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RESEARCH

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Integration of disamenity costs and equality considerations regarding onshore wind power expansion and distribution into energy system optimization models

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Abstract

Background Social acceptance of energy infrastructure projects affects public support for the energy transition and is essential for the transition's sustainability and success. Despite extensive research focusing on the social acceptance of renewable energy, and on the acceptance of onshore wind power in particular, energy system models have largely prioritized techno-economic aspects. This focus has created a gap between model results and decision-makers' needs. In this study, we offer recommendations for integrating disamenity costs and equality considerations—two critical social aspects related to onshore wind power—into energy system optimization. To achieve this, we use a spatially distributed model from a climate-neutral Germany and explore various implementations and trade-offs of these two social aspects.

Results We identified effective linear formulations for both disamenity costs and equality considerations as model extensions, notably outperforming quadratic alternatives, which exhibit longer solution times (+50–115%). Our findings reveal that the endogenous consideration of disamenity costs in the optimization approach can significantly reduce the human population's exposure to wind turbines, decreasing the average disamenity per turbine by 53%. Drawing on notions of welfare economics, we employ two different approaches for integrating equality into the optimization process, permitting the modulation of the degree of equality within spatial distributions in energy system models. The trade-offs of the two social aspects compared to the cost-optimal reference are moderate, resulting in a 2–3% increase in system costs.

Conclusions Disamenity costs emerge as a predominant factor in the distribution of onshore wind power in energy system optimization models. However, existing plans for onshore wind power distribution in Germany underscore equality as the driving factor. The inclusion of social aspects in energy system models facilitates the identification of socially superior wind turbine locations. Neglecting disamenity costs and equality considerations leads to an overestimation of the practical solution space for decision-makers and, consequently, the resulting energy system designs.

Keywords Energy system modeling, Spatial distribution, Wind power, Optimization, Social acceptance, Disamenity costs, Equality

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Background

The focus of this study is the integration and co-optimization of social aspects concerning the expansion and distribution of onshore wind energy within a spatially distributed energy system model. Social acceptance of energy infrastructure projects affects public support for the energy transition [1–4] and is, therefore, a precondition for its sustainability and success. Due to substantial land area requirements, renewable energy sources change the living environment of many people [5]. Consequently, rising opposition from local groups has the potential to derail national goals [6]. In the past, infrastructure projects entailing the expansion of renewable energy and transmission grids have faced delays in Europe [7, 8] and the United States [9]. In addition, societal consent remains crucial as future energy transition phases involve the transformation of transportation, heating, and industrial processes, each requiring extensive and diverse stakeholder participation.

While energy system models have traditionally prioritized easily quantifiable techno-economic aspects [10, 11], research on the social acceptance of renewable energy is also ample, with onshore wind power being the most commonly addressed technology [2, 12]. In the present article, we explore two social aspects related to community acceptance of onshore wind power [13]: first, we examine disamenity costs to address local opposition directly, and second, we consider equality as part of the general allocation and as a proxy for a just distribution.

Local opposition decreases the success rate of energy infrastructure projects and often stems from the perceived adverse effects of nearby wind turbines on the local human population [14]. In particular, local disamenities caused by noise emissions, flicker, and an impact on scenic landscapes represent one facet of onshore wind power´s externalities, as do threats to wildlife [12, 15]. Therefore, disamenity costs are a way to internalize this external effect and, if considered, can contribute to socially accepted siting decisions [16]. However, considering the disamenity comes at the cost of utilizing more sites with less advantageous wind conditions. Disamenity costs have been applied primarily in research on onshore wind power. Weinand et al. [17] highlighted the importance of disamenity in historical siting decisions in Europe. In a German case study, Lehmann et al. [16] found that local disamenity dominates the socially optimal allocation of wind turbines due to a larger spatial variability than conventionally applied generation costs. Ruhnau et al. [15] provided a European-wide data set of disamenity costs based on turbine distance and population density. Furthermore, they concluded that including disamenity costs does not significantly affect onshore wind power economics in most European countries but is a means to reduce the exposure of the human population to wind power sites. Further studies have analyzed the trade-offs between conventional generation costs, disamenity costs, and other externalities [18–21]. To the best of the authors' knowledge, research on disamenity costs involving energy system models remains limited. Price et al. [22] showed that considering scenic landscapes in Great Britain can increase the costs of the power system by 14%. Grimsrud et al. [23, 24], as well as Lohr et al. [25], applied a broader definition of environmental costs and found that the inclusion of these costs can significantly alter the distribution or, respectively, mitigate environmental degradation. However, data on disamenity costs has not previously been integrated into an energy system model [15].

In addition to direct exposure, the perception of the fairness of the distribution and the associated decision-making process also influences project acceptance [26]. In a qualitative study in Bavaria, Langer et al. [27] showed how an unequal distribution fosters envy, generating a feeling of injustice. Surveys in Germany confirmed the significance of equality in conjunction with efficiency in siting questions [28, 29], which is often overlooked in most energy system models. Based on Vågerö and Zeyringer´s energy justice perspectives framework [11], equality can be classified as an equity principle of distributional justice, which is most often applied in spatial contexts in energy system models. Despite variations in equality definitions (equity factors), trade-offs between these two principles—efficiency (i.e., cost-optimality) and equality—have been explored, often using modeling-to-generate alternative methods [30]. Sasse and Trutnevyte [31] compared a cost-optimal energy system design for Central Europe in 2035 with one characterized by evenly distributed system costs. In another Swiss study [32], the researchers used ratios of renewable capacity and population size or electricity demand as equity factors. Neumann [33] analyzed the additional costs for a highly renewable energy system in Europe associated with a nationally balanced generation and consumption, as opposed to a cost-optimal approach, emphasizing an equity principle that included the factor of responsibility. Furthermore, flat near-optimal solutions of energy system designs, which enable the consideration of broad technology configurations [34] and spatial diversity [35], suggest that including other objectives may only moderately increase system costs. Despite the highlighted edge cases of research, including efficiency and equality, as well as the presumably ample solution space, equality as a decision criterion is still lacking in the optimization process, either being entirely enforced or discussed ex-post [11, 18, 36].

Energy system models serve as valuable tools for gaining insight into the dynamics of renewable energy systems and assisting decision-makers in the energy policy domain to establish a secure and affordable energy supply [1]. However, an exclusive focus on techno-economics while neglecting environmental and social factors may result in undesirable or infeasible outcomes, such as extreme spatial concentration [37], leaving decision-makers without the information they need [10, 11, 36, 38]. In this contribution, we strive to enhance energy system optimization models, transforming them into more effective instruments for policy advice by addressing the social factors involved in energy infrastructure. Therefore, we endogenously incorporate the social aspects of onshore wind power into the optimization process and apply it to an energy system model for a climate-neutral Germany. The primary objective of this study is to offer practical recommendations for the implementation and parametrization of disamenity costs and equality in energy system optimization models, considering the context and available resources. To do so, we integrate an openly accessible data set of European disamenity costs related to onshore wind power into an energy system optimization model and test different model implementations. Furthermore, we link spatially distributed energy system optimization with the field of welfare economics. Through the application of social welfare functions, we offer a theoretical motivation for the equal distribution of onshore wind power and compare two different implementation approaches, modulating different levels of equality. In addition, we briefly analyze the impact of these two social aspects on the expansion and distribution of onshore wind power in a climate-neutral Germany, including relevant trade-offs.

The remainder of the article is structured as follows. Sect. "Methods" provides an overview of the applied energy system optimization model, as well as the proposed implementations of the two social aspects: disamenity costs and equality. In Sect. "Results", we first present the impact of these social aspects on the energy system and then compare and evaluate their different implementations. Sect. "Discussion" is devoted to recommendations and limitations regarding the implementations and may serve as a guide for energy system modelers. Finally, we present our conclusions and identify avenues of future research in Sect. "Conclusion".

Methods

This section first presents a brief overview of the reference model applied. In the following subsections, we explain the additional model features that are the focus of this study—the implementation of disamenity costs and the consideration of equality, which are two social aspects related to onshore wind power.

Model and data

Model

We apply the energy system optimization model adopted from Lohr et al. [25] and based on the ESTRAM framework, which minimizes the total system costs C^{sys} to cover the hourly end energy demand of Germany in a climate-neutral scenario for the period of 1 year. The general formulation of the cost function is described in Eq. 1. It comprises the capital expenditures (Capex) and operation and maintenance costs (O&M costs) for components as well as the costs for energy carriers, aggregated over all model regions k. Here, $P^{\text{cap}}_{c,k}$ describes the installed capacity of component c with the specific installation costs c^{fix}_c, the capital recovery factor β^{crf}_c, and the specific O&M costs c^{om}_c; $E^{\text{import}}_{e,k}$ is the imported energy of energy carrier e with corresponding specific costs c^{car}_e:

$$C^{\text{sys}} = \sum\nolimits_k \Big(\sum\nolimits_c P^{\text{cap}}_{(c,k)} \cdot c^{\text{fix}}_c \cdot (\beta^{\text{crf}}_c + c^{\text{om}}_c) + \sum\nolimits_e E^{\text{import}}_{(e,k)} \cdot c^{\text{car}}_e\Big) \tag{1}$$

In the present study, we use the model with this objective function as a (cost-optimal) reference, which we amend by the additional equations introduced in Sects. "Disamenity costs" and "Equality". Furthermore, for the purpose of the research questions, we modify the previously published model as described below.

As in the model we adopted from Lohr et al. [25], we fix the capacity and the location of all *other* renewable sources (biomass, hydropower, photovoltaic (PV), and offshore wind); however, for onshore wind power, we optimize the capacity expansion and distribution model-endogenously. Consequently, the relevant system costs that are subject to the optimization comprise the Capex and O&M costs for onshore wind power, energy storage, and sector-coupling system components, as well as the import costs for the energy carrier hydrogen (H_2). H_2 imports serve primarily as slack to compensate for onshore wind energy with a lower economic value. In contrast, utilizing other flexible components, such as battery storage or electrolysis, helps balance different spatial distribution patterns. The flexibility options not considered in this study are electricity import, demand-side management, or load shedding.

Regarding spatial resolution, we increase the number of nodes K from the 16 federal states to the 38 regions of the NUTS2 level. This increase is accompanied by

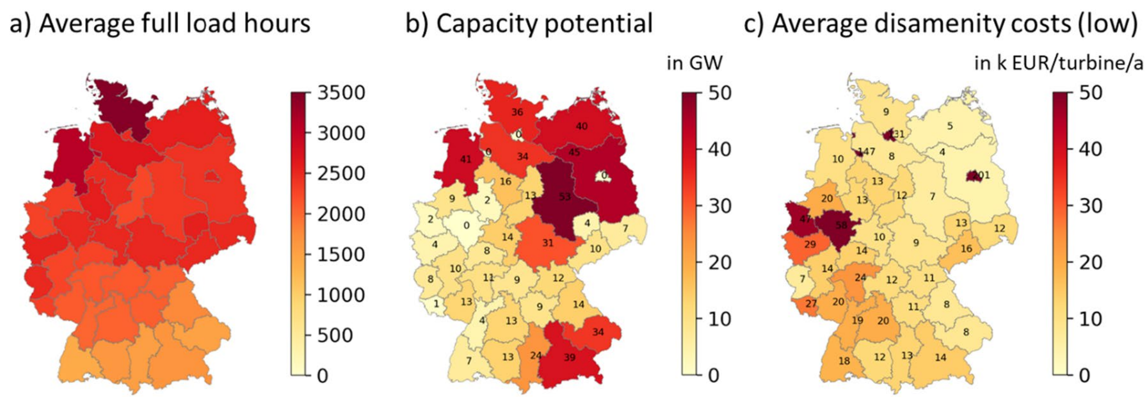

Fig. 1 Distribution per model region of (**a**) wind resources in average full load hours per year, (**b**) onshore wind power capacity potential, and (**c**) average disamenity costs ('Low' scenario) of the considered potential with a reference turbine rated power capacity of 2 MW

a finer resolution of the transport grids, particularly a stronger emphasis on the bottlenecks of the electricity grid[1] and the impeded import of H_2, which we limit to existing gas hubs [39].

Data

We use the same end energy consumption and renewable potential as in the adopted model [25], based on Prognos et al. [40]. This includes the aggregated demands for electricity (672 TWh), district heating (133 TWh), combined H_2 and methane (259 TWh), oil (301 TWh), and biomass (68 TWh). The total installed capacity of renewable sources comprises 385 GW of PV, 70 GW of offshore wind power, 4 GW of hydropower, and a biomass potential of 347 TWh. To ensure coherence with the data on disamenity costs (introduced in Sect. "Disamenity costs"), we determine the capacity potential of onshore wind power relying on the available data set by Ruhnau et al. [15], which was derived from Ryberg et al. [41]. Due to low setback distances, the estimated potential of nearly 600 GW can be considered high. Figure 1 shows the spatial distribution of the most relevant model inputs regarding onshore wind power.

Furthermore, we allow a constant import of H_2 for 90 EUR/MWh (3 EUR/kg) and take other technologies and their corresponding parameters from Lohr et al. [25].

Disamenity costs

Data

Disamenity costs are the quantification of the perceived adverse effect of onshore wind turbines on the local human population; thus, they are difficult to objectify but enable comparison with conventional generation costs. In this study, we use a Europe-wide open data set by Ruhnau et al. [15], which is based on the proximity of human settlement to potential turbine sites. Krekel and Zerrahn [14] set a threshold of 4 km, beyond which no disamenity costs can be expected. At a shorter distance of 1 km, based on lower-case scenario assumptions, they estimated annual costs of 5 EUR per person per turbine. For the minimum setback of 0.2 km, the annual cost was estimated at 10.8 EUR per person per turbine. Given the high uncertainty, Krekel and Zerrahn provided an upper-case estimation, assuming costs ten times higher. Combining the cost function with the population density, they determined the disamenity costs of nearly 300,000 potential turbine sites in Germany. Other external effects of onshore wind power, such as the impact on biodiversity or whether the affected landscape is particularly scenic, were not considered.

Unlike the potential turbine sites in the data set, the applied energy system is not spatially explicit. Therefore, we process the raw data and assign all potential turbine sites to a model region. Because turbines cannot be considered individually within a model region k, we sort the turbines by increasing disamenity costs and determine aggregated marginal disamenity cost curves as a function f_k^{DC} of the installed capacity P_k^{cap} (an example for the federal state of North Rhine–Westphalia is illustrated in Fig. 2 [red line]). Consequently, we assume a strict order of installations from small to high disamenity costs. We integrate the marginal disamenity cost function to derive the total disamenity costs of a region C_k^{DC} (Eq. 2). Figure 1c illustrates the spatial heterogeneity of the average turbine disamenity costs of the (fully utilized) capacity potential of onshore wind power for all model regions.

[1] The model does not optimize transmission expansion endogenously but considers planned transmission grid expansion.

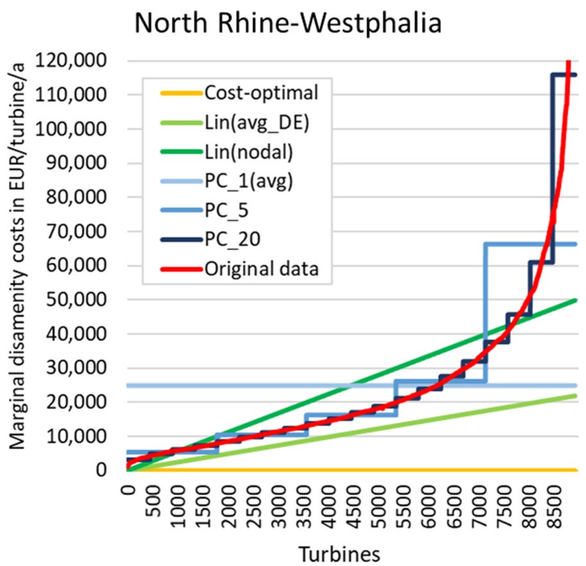

Fig. 2 Implemented marginal disamenity cost functions ('Low' scenario) for North Rhine-Westphalia as an example of a federal state with high population density. We use a reference turbine with a rated power capacity of 2 MW

$$C_k^{\mathrm{DC}} = \int_0^{P_k^{\mathrm{cap}}} f_k^{\mathrm{DC}}\left(P_k^{\mathrm{cap}^*}\right) dP_k^{\mathrm{cap}^*} \forall k \tag{2}$$

The addition to the objective function involves aggregating the disamenity costs across all model regions to calculate the total disamenity costs C^{DC} (Eq. 3):

$$C^{\mathrm{DC}} = \sum_k C_k^{\mathrm{DC}} \tag{3}$$

Implementations

To include the aspect of disamenity in the optimization model, we add the disamenity costs C^{DC} to the system costs, deriving the total costs as the new objective function (Eq. 4):

$$C^{\mathrm{total}} = C^{\mathrm{sys}} + C^{\mathrm{DC}} \tag{4}$$

As Eq. 2 is a non-linear function, which is challenging to implement in energy system optimization models, we test various approximations in this study. As a first implementation, *Lin(nodal)*, we try a linear interpolation $f_k^{\mathrm{DC,lin\_nodal}}$ of the regional marginal disamenity cost function f_k^{DC}, which is described in the following equation:

$$f_k^{\mathrm{DC,lin\_nodal}} = 2 \cdot \frac{C_k^{\mathrm{DC,max}}}{p_k^{\mathrm{max}}} \cdot \frac{P_k^{\mathrm{cap}}}{p_k^{\mathrm{max}}} \forall k \tag{5}$$

Therefore, we normalize the slope by the total disamenity costs $C_k^{\mathrm{DC,max}}$ of the capacity potential p_k^{max}, representing the accumulated disamenity costs of a region, wherein all potential turbine sites are utilized. By integrating Eq. 5 (cf. Equation 2), we derive the corresponding disamenity cost function (Eq. 6). To finally include the social aspect of disamenity in the optimization model, we sum across all model regions k and add the total to the objective function (Eq. 1):

$$C_k^{\mathrm{DC,lin\_nodal}} = C_k^{\mathrm{DC,max}} \cdot \frac{P_k^{\mathrm{cap}2}}{p_k^{\mathrm{max}2}} \forall k \tag{6}$$

For the second implementation, *Lin(avg_DE)*, we assume a homogenous disamenity cost distribution across the potentials of all regions, using the average disamenity costs of the total potential of Germany (see Eq. 7). This formulation resembles the environmental costs introduced in a former publication [37] and allows us to determine the value of spatially resolved data:

$$C_k^{\mathrm{DC,lin\_avg}} = \left(\frac{\sum_\kappa C_\kappa^{\mathrm{DC,max}}}{\sum_\kappa p_\kappa^{\mathrm{max}}}\right) \cdot \frac{P_k^{\mathrm{cap}2}}{p_k^{\mathrm{max}}} \forall k \tag{7}$$

Although integrating these two implementations does not require additional constraints, the terms added to the objective function are quadratic and, accordingly, may complicate the process of solving the optimization problem. Consequently, we provide three more implementations, which use a piecewise-constant approximation of Eq. 2 and do not convert the linear optimization problem (LP) to a quadratic optimization problem (QP). Therefore, we segment the function in equidistant intervals $i \in \{1, \ldots, I\}$, which requires additional variables $P_{k,i}^{\mathrm{cap}}$ per segment. Equation 8 contains the relation of the total and the segmented installed capacity of onshore wind power in a region. Equation 9 adjusts the bounds of the segmented capacity potential, respectively:

$$P_k^{\mathrm{cap}} = \sum_i P_{k,i}^{\mathrm{cap}} \forall k \tag{8}$$

$$P_{k,i}^{\mathrm{cap}} \leq \frac{p_k^{\mathrm{max}}}{I} \forall k, \forall i \tag{9}$$

The resulting disamenity cost function, described in Eq. 10, is the sum of all intervals, each with individual but constant marginal disamenity costs $f_{k,i}^{\mathrm{DC,pc\_I}}$:

$$C_k^{\mathrm{DC,pc\_I}} = \sum_i P_{k,i}^{\mathrm{cap}} \cdot f_{k,i}^{\mathrm{DC,pc\_I}} \forall k \tag{10}$$

Table 1 Overview of all implemented marginal disamenity cost functions

Marginal disamenity cost function	Objective function	Model additions			Description	Data scenarios
		Vars	Cons	Params		
Cost-optimal	Equation 1 (LP)	–	–	–	Reference without disamenity costs	–
Lin (avg_DE)	Equation 1 + *Eq. 7 (QP)	0	0	1	Linear interpolation based on the average of Germany	Low, high
Lin (nodal)	Equation 1 + *Eq. 6 (QP)	0	0	K	Linear interpolation based on regional data	Low, high
PC_1 (avg)	Equation 1 + *Eq. 10 (LP)	1 K	K + 1 K	K	Average based on regional data	Low, high
PC_5	Equation 1 + *Eq. 10 (LP)	5 K	K + 5 K	5 K	Piecewise-constant interpolation based on regional data with 5 intervals	Low, high
PC_20	Equation 1 + *Eq. 10 (LP)	20 K	K + 20 K	20 K	Piecewise-constant interpolation based on regional data with 20 intervals	Low, high

* The addition to the objective function involves the aggregation of the disamenity costs across all model regions, as in Eq. 3

Eq: equation; Vars: number of variables; Cons: number of constraints; Params: number of parameters; K: number of model regions

As for the linear-increasing implementations, we normalize the marginal disamenity costs $f_{k,i}^{\mathrm{DC,pc\_I}}$ with the original disamenity costs (cf. Equation 2) for a full utilization—of an interval i, in this case—as in the following equation:

$$f_{k,i}^{\mathrm{DC,pc\_I}} = \frac{I}{p_k^{\max}} \cdot \left[C_k^{\mathrm{DC}}\left(x \cdot \frac{p_k^{\max}}{I}\right) \right]_{x=i-1}^{x=i} \quad \forall k, \forall i \qquad (11)$$

In this study, we test implementations of twenty (*PC_20*) and five (*PC_5*) intervals, as well as only one interval (*PC_1(avg)*), which coincides with the assumption of homogeneous (average) disamenity costs within one region. Table 1 provides an overview of all implementations, and Fig. 2 visually displays the marginal disamenity cost functions for the example of the federal state of North Rhine-Westphalia. In addition to the lower valuation, we also test the higher valuation of disamenity costs (ten times higher) from Ruhnau et al. [15] to account for the high uncertainty of quantifying human preferences regarding wind turbine exposure.

Equality

Theory

The distribution of renewables among regions in spatially distributed energy system optimization models qualifies as a multiagent resource allocation problem [42]. However, most models that adopt the perspective of a central planner fail to address this, neglecting heterogeneous stakeholders (agents). For example, local politicians advocating for their regions' interests may not agree with the most efficient outcome, which often features an extreme distribution of renewables [37]. Consequently, the associated energy system design from model results may be undesirable, if not politically infeasible. Promoting an alternative with potentially higher acceptance but increased system costs, research has emerged that studies the gap between efficient design solutions and equally spatially distributed renewables [32].

In this study, we want to explore the intermediate space between efficient and equal distribution, i.e., integrating equality into optimization without enforcing it entirely. To establish better or more desirable outcomes, we must assess the overall quality of a distribution, such as through applying collective utility functions [42]. The field of welfare economics offers methods to quantify interpersonal utility, called social welfare functions, which have been applied in the field of computer science [43]. The present approach of a central planner in energy system models reflects the utilitarian social welfare function that sums up all individuals' utility with no regard for distributional effects. On the other hand, an equal distribution aims to maximize the egalitarian social welfare function, focusing on maximizing the lowest utility of an individual[2] [42]. Both approaches are relevant benchmarks but represent extremes in welfare economics and, hence, are often suboptimal in practice.

Therefore, the cost-optimal solution (cf. Sect. "Model") representing an efficient or utilitarian approach serves as the first extreme of the solution space. For all other solutions, we compare the regions, taking their capacity potential utilization (CPU) γ_k as the equity factor. By including the potential $p_k^{\max}$, we consider the heterogeneous conditions of the regions dedicating their land area to onshore wind power (Eq. 12) and, thus, also address a capability-oriented equity principle approach [11]. Furthermore, we choose the capacity potential as a standard parameter in energy system models, thus ensuring generally feasible solutions [25]. Other equity factors, such as those based on population or land area, can be applied similarly but may produce conflicts when model

[2] This assumes homogeneous preferences across regions.

regions are heterogeneous, requiring careful case-by-case examination:

$$\gamma_k = \frac{P_k^{\text{cap}}}{p_k^{\text{max}}} \forall k \tag{12}$$

For the second extreme solution (egalitarian), we define in Eq. 13 that all regions must dedicate the same share of their potential (eligible land area), equal to the global capacity potential utilization $\overline{\gamma}$, which serves as a control variable, as defined in Eq. 14. Despite the fixed distribution shares of onshore wind power, the total expansion can be lower or higher and, like other variables (H_2 import, energy storage, and sector-coupling), is subject to cost-optimization:

$$\gamma_k = \overline{\gamma} \forall k \tag{13}$$

$$\overline{\gamma} = \frac{\sum_k P_k^{\text{cap}}}{\sum_k p_k^{\text{max}}} \tag{14}$$

Equality, meaning the equal capacity potential utilization or equal distribution of onshore wind power in our specific case, pronounces a just distribution to be a desirable objective in itself. However, in terms of local utility, it can be argued that the "average" utilization of a given potential ensures value creation while simultaneously not overburdening a given region compared to others.

Implementations

We introduce two implementations relying on different model approaches to include equality in energy system optimization without enforcing it completely. The first (*Min var*) values a more equal distribution as an objective (Eq. 15). Therefore, this approach conflicts with efficient distribution and, thus, with the objective of cost minimization:

$$C^{\text{total}} = C^{\text{sys}} + C^{\text{ineq}} \tag{15}$$

A deviation of the K region's capacity potential utilization γ_k to the global capacity potential utilization $\overline{\gamma}$ increases the social costs of the solution, which we define as inequality costs C^{ineq}. We use the variance as the measure for their calculation and weigh it with the parameter c^{eq} (see Eq. 16) to add the term to the model's objective function:

$$C^{\text{ineq}} = c^{\text{eq}} \cdot \frac{1}{K} \cdot \sum_k (\gamma_k - \overline{\gamma})^2 \tag{16}$$

Consequently, setting $c^{\text{eq}} = 0$ provides a cost-optimal solution, whereas $c^{\text{eq}} \to \infty$ results in equal distribution, and any other value leads to a co-optimization of system costs and inequality costs. Furthermore, analogous to the individuals in the social welfare functions, we weigh every region equally, neglecting varying populations and sizes. Disamenity costs follow the behavior pattern of homo economicus (the fewer installations, the better); in contrast, the relative appraisal of local onshore wind power installation, involving a comparison with other regions reflects the model of homo reciprocans [44], which may acknowledge procedural and distributive justice as important drivers of social acceptance. However, the variance in the mathematical formulation comes with quadratic terms and converts the cost-optimal (or equal) LP to a QP.

As an alternative (*Lim d*), we add constraints to the model to limit the deviation of the regional capacity potential utilization γ_k. In Eq. 17, we set upper and lower bounds that form intervals depending on the maximum deviation parameter d and based on the global capacity potential utilization $\overline{\gamma}$. Regardless of the chosen parameter value, our formulation generally requires any region to contribute ($\gamma_k > 0$). This approach keeps the original cost-optimal objective function (Eq. 1) and maintains the optimization as an LP, as it reduces only the solution space and, hence, can limit inequality. However, equality is no longer considered a decisive criterion within the feasible space:

$$(1 + d) \cdot \overline{\gamma} \geq \gamma_k \geq \frac{\overline{\gamma}}{(1 + d)} \forall k \tag{17}$$

Table 2 provides a tabular overview of the model approaches, while Fig. 3 contrasts the implementations schematically. For both model approaches, the values for the parameters c^{eq} and d determine the level based on the extent to which equality is considered in the optimization process. We note that, similar to the general choice of a social welfare function, any value for a parameter (including the extremes for the cost-optimal and equal distribution) embodies a value judgment [11]. Furthermore, we omit disamenity costs for the sake of simplicity.

To measure and assess different levels of equality for both approaches, we choose the relative standard deviation (RSD), also referred to as the coefficient of variation, as the (in-)equality measure. The RSD is defined as the ratio of the standard deviation to the mean of a distribution. Relating it to the mean enables the comparison of dispersions in different distributions. Similar to the standard deviation, the RSD of an equal distribution is 0, whereas there is no upper limit for a high variability. Using the standard deviation, defined as the square root of the variance, to minimize the variance, as in the *Min var* approach can efficiently address inequality, providing Pareto-optimal results.

Table 2 Overview of all implemented modeling approaches to considering equality, as well as the two extreme solutions and their corresponding theoretical parameter values, which we did not apply in practice

Modeling approach	Objective function	Model additions		Description	Parameters
		Vars	Cons		
Cost-optimal	Equation 1 (LP)	–	–	Reference: cost-optimal solution without considering equality representing utilitarian extreme	$c^{eq} = 0$ $d \to \infty$
Equal	Equation 1 (LP)	K + 1	2 K + 1	Reference: solution with equal regional CPU as the egalitarian extreme	$c^{eq} \to \infty$ $d = 0$
Min var	Equation 1 + Eq. 16 (QP)	K + 1	K + 1	Co-minimization of the variance of regions' CPU and total system costs	$c^{eq} \in [10^9, 10^{12}]$
Lim d	Equation 1 (LP)	K + 1	3 K + 1	Limit the deviation of regions' CPU	$d \in [0.05, 3]$

Eq: equation; Vars: number of variables; Cons: number of constraints; CPU: capacity potential utilization

Results

This section first provides an overview of the expected level of influence on the energy system when incorporating the presented social aspects of onshore wind power. Then, we compare the different implementations of disamenity costs and equality from a methodological perspective and describe their impact on the model performance.

Impact of disamenity costs and equality

This first part of this chapter presents the contextual contribution of incorporating disamenity costs and equality regarding onshore wind power distribution and expansion in a climate-neutral Germany. The section first describes the impact on the energy system and then the trade-offs between system costs, disamenity costs, and equality.

Integrated energy system overview

We compare the cost-optimal solution with the solutions of piecewise-constant interpolation of disamenity costs (*PC_20*) and the equal distribution of onshore wind power (*Equal*) to demonstrate the general impact of the two social aspects on the energy system of a climate-neutral Germany from a contextual point of view. Therefore, we differentiate between the data scenarios 'Low' and 'High' for disamenity costs, in accordance with Ruhnau et al. [15], and focus on the implementation with the most data points (*PC_20*). In contrast to the integration of disamenity costs, we confine the inclusion of equality to the extreme solution. Figure 4 provides an overview comparing a) the primary energy and b) the total system costs.

As we fixed the biomass potential and the installed capacity of hydropower, PV, and offshore wind, the primary energy supply of these renewable sources remains unchanged throughout all solutions. Low disamenity shows a neglectable impact on the energy supply

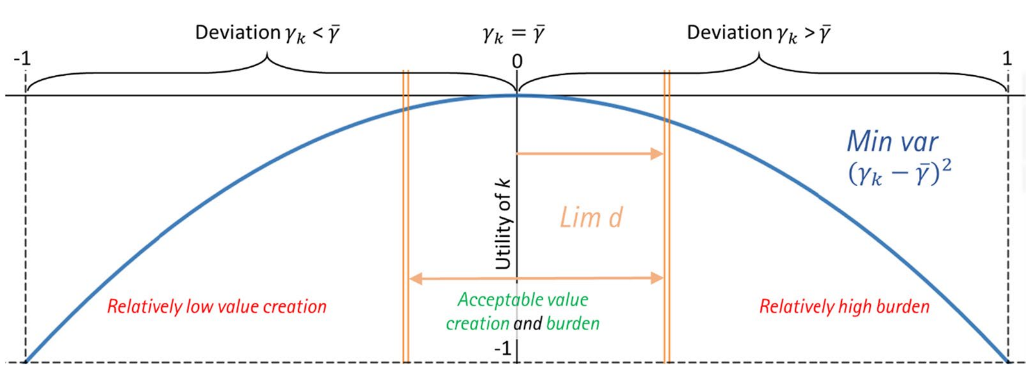

Fig. 3 Exemplary schema illustrating the two modeling approaches to include equality in the model: first, the quadratic characteristic of the objective function (blue) for the *Min var* modeling approach when a region's capacity potential utilization deviates from the global mean. A negative utility induces inequality costs in our model. Second, a limitation of the deviation from the global mean (orange) is implemented as a model constraint, representing the *Lim d* modeling approach (no utility or inequality costs considered). Note: due to the dependency of the two variables γ_k and $\overline{\gamma}$, the length of the available interval for the resulting deviation is always < 1

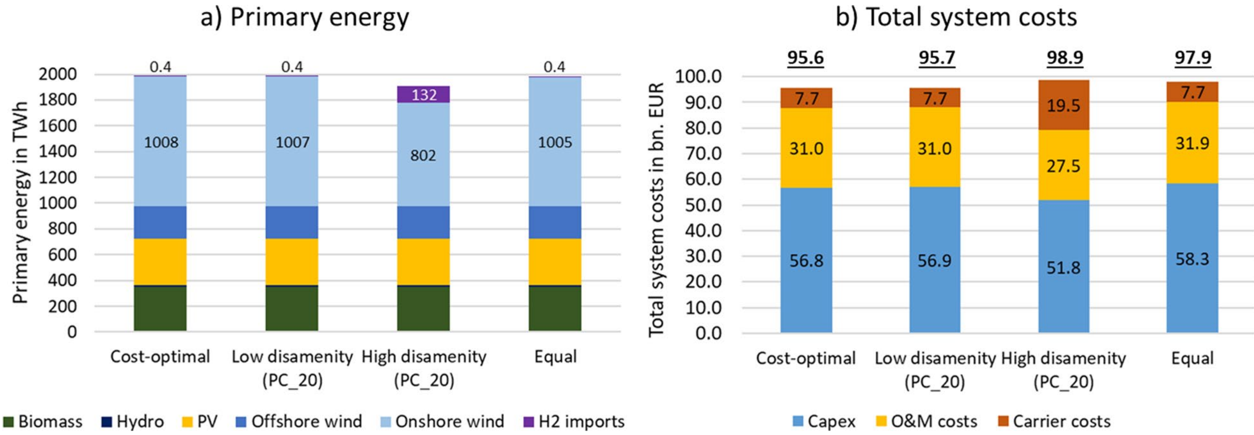

Fig. 4 Comparisons of (**a**) primary energy and (**b**) total system costs when including the suggested social aspects of disamenity costs and equality. The total system costs also comprise non-optimized elements, such as the Capex and O&M costs of other renewable energy sources and the utilization of biomass (energy carrier)

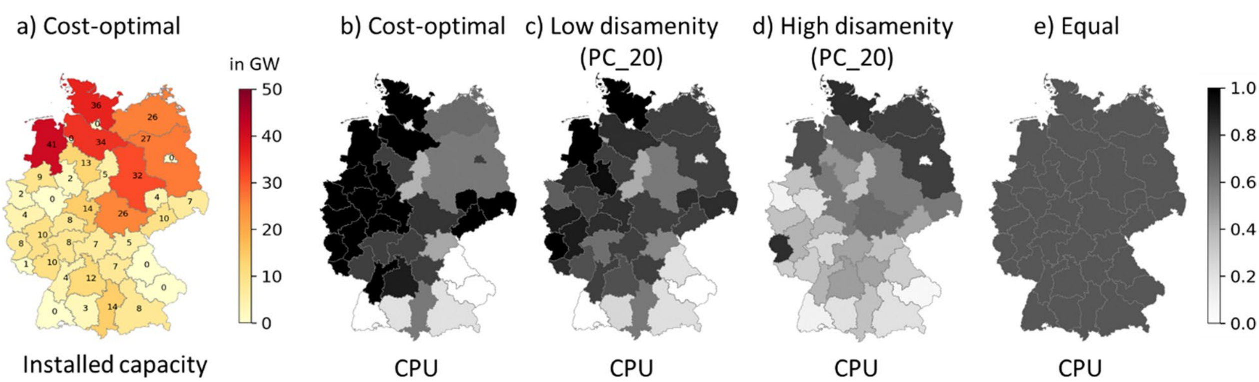

Fig. 5 Spatial distribution of onshore wind power by (**a**) the installed capacity of the cost-optimal solution and (**b**–**e**) the capacity potential utilization (CPU) of the other highlighted solutions

compared to the cost-optimal results, whereas the higher resistance toward the installation resulting from high disamenity reduces the overall energy output of onshore wind power by 20%. Importing H_2 compensates for this, which shifts the cost structure and increases the total system costs by 3.3 bn. EUR. An equal distribution of onshore wind power has a limited impact with nearly the same primary energy supply. However, the lower efficiency of turbine siting requires the installation of more turbines and comes with additional costs of 2.3 bn. EUR. Despite the conflicting or constraining effect of disamenity costs and equal distribution, onshore wind power remains competitive compared to H_2 imports and continues to provide the highest supply of renewable energy in our scenario. This holds even with a reduced import price of H_2 from 90 to 60 EUR/MWh (cf. Figure A.1 in the Appendix).

We illustrate the spatial distribution of onshore wind power in Fig. 5. In the cost-optimal solution, wind turbines utilize 400 GW of the total 600 GW potential. Therefore, most installations are in the north and northeast, similar to the given capacity potential. In contrast, the highest capacity potential utilization is in the west, whereas the high energy surplus in the northeast and unfavorable wind resources in the south induce lower utilization rates. Compared to the cost-optimal solution, taking into account low disamenity slightly reduces the capacity potential utilization in the west and in Saxony in the east and shifts turbines in more sparsely populated regions in the northeast. While the distribution with low disamenity resembles the cost-optimal distribution, the high valuation of disamenity reduces the onshore wind power capacity by 92 GW. In addition, the turbine allocation is inverse to the regional disamenity costs (cf. Figure 1c) and, thus, is dominated by it, as indicated in previous research [16]. Unlike the enforced equal distribution, the impact of disamenity costs on the distribution decreases if the

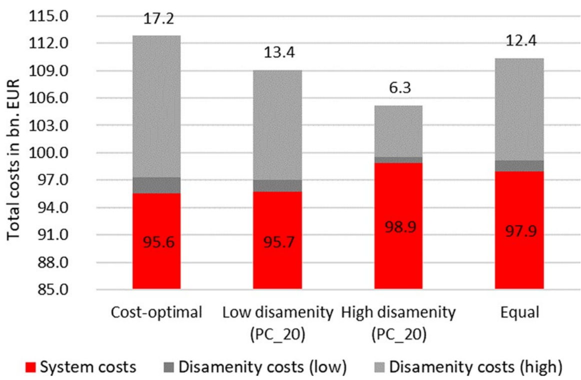

Fig. 6 Comparisons of the total costs for the four highlighted solutions. The total costs consist of system costs (red) and projected disamenity costs of onshore wind power (gray) for the data scenarios 'Low' and 'High'

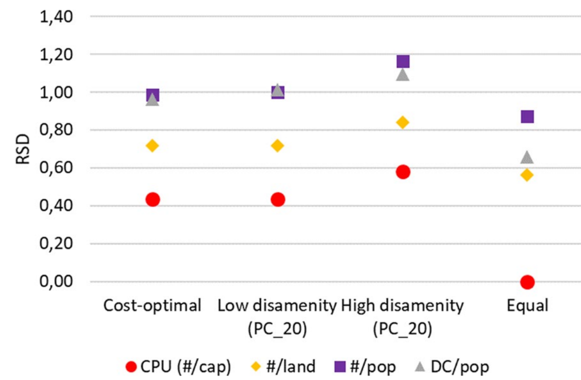

Fig. 7 Comparison of the different levels of equality for the four highlighted solutions based on the relative standard deviation (RSD) for various equity factors: '#/cap'—number of turbines per capacity potential (applied in this study), '#/land'—number of turbines per land area, '#/—number of turbines per population, 'DC/pop'—disamenity costs per population

siting has more flexibility, as in a scenario with more imported H_2 when a smaller share of the capacity potential is utilized (see Appendix Figure A.2).

Trade-offs between objectives

The different solutions for the distribution of onshore wind power come with trade-offs regarding relevant objectives, namely system costs, disamenity costs, and their level of equality regarding wind turbine allocation. Figure 6 illustrates the total costs of the different solutions, consisting of the system costs (cf. Equation 1) and the projected disamenity costs for the onshore wind power distributions. We use each solution's regional expansion results to derive comparable disamenity costs and calculate effective disamenity costs based on the original disamenity cost function, as in Eq. 2. The cost-optimal solution causes the highest disamenity costs at 17.2 bn. EUR based on a high disamenity valuation (or 1.7 bn. EUR for a low valuation), which is equivalent to 17 EUR/MWh per supplied onshore wind energy[3] (on average). Even considering a low valuation of disamenity in the optimization [*Low disamenity (PC_20)*] with nearly the exact total system costs and total installations of onshore wind power as the cost-optimal solution, reallocating turbines reduces the effective disamenity costs by 22%. However, a further reduction of the effective disamenity costs, as in the *High disamenity (PC_20)* solution (-63%), cannot be achieved through better siting but comes with a significantly lower number of installed wind turbines, which also affects the system economically.[4]

Notably, the assessment of the different solutions based on this total cost definition is highly impacted by the uncertainty in the valuation of disamenity (represented by the data scenarios). Comparing the two common solutions in the literature, *Cost-optimal* and *Equal*, the first is favored for a low valuation of disamenity (includes dark gray bar), whereas the latter is preferred for a high valuation (includes dark and light gray bar). It should be noted that through an increased supply from other energy sources, the expansion level of onshore wind power can be lowered, significantly mitigating disamenity. This is illustrated in the Appendix (see Figure A.3) for a scenario of cheaper imports of H_2, which features an expansion of 237 GW (*Cost-optimal* and *Equal*) and 147 GW (*High disamenity*).

Figure 7 compares the different equality levels provided by the four solutions based on the RSD as the inequality measure. The red marker illustrates the definition of equality, which in this study, is the capacity potential utilization of each model region (equal to the number of wind turbines per potential). For the scenario of a climate-neutral Germany, the solution based on our equality definition (*Equal*) provides the highest level of equality, not only for the imposed turbines per potential but also per land area and per population. However, due to the homogeneous potential distribution across regions, including outliers, the inequality level based on turbines per land area (yellow) is close to that of the other solutions. In addition, the distribution of disamenity (gray) among the population may be perceived as the most equitable for this solution, particularly contrasting the inequality of the *High disamenity* solution. However, this reveals a trade-off between these two aspects, as the

[3] In comparison, the average generation costs for onshore wind power are roughly double the disamenity costs (between 31 and 34 EUR/MWh).

[4] The achieved reduction in disamenity costs aligns with the observation of Ruhnau et al. [15], who analyzed the disamenity and levelized cost of electricity of onshore wind power and found exposure to be reduced by 30–60%, although for lower expansion levels.

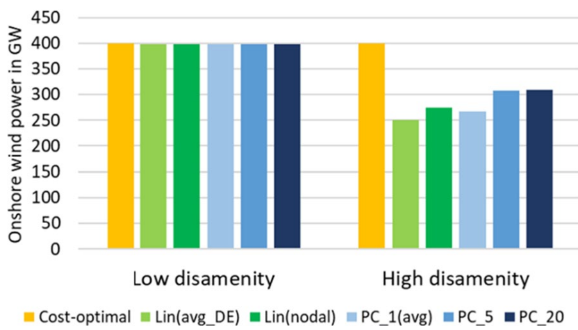

Fig. 8 Total installed capacity of onshore wind power by implementation for the two disamenity data scenarios 'Low' and 'High'

absolute disamenity of the *Equal* solution is two times higher (cf. Figure 6).

Section "Efficacy" presents further trade-offs between different levels of equality and system costs.

Implementation comparison: disamenity costs

This section presents the differences between the disamenity cost implementations (cf. Table 1 in Sect. "Implementations") based on the model results for onshore wind power expansion and distribution, as well as their efficacy and accuracy compared to the approximated original data.

Onshore wind power expansion and distribution

The implementations have varying marginal disamenity cost functions (see Fig. 2) influencing the value of onshore wind power, which results in differing expansion and distribution. However, a low valuation of disamenity provides no significant changes to the cost-optimal reference, with a decreased capacity in the range of only 1.3 to 1.7 GW (see Fig. 8). If we assume high disamenity, the total installed capacity is reduced by at least 23%, although differences between the implementations exist: with piecewise-constant marginal cost functions (*PC_5*, *PC_20*), the contribution of onshore wind power is the highest, sharing the same expansion level. The other two implementations, which consider (coarser) nodal heterogeneity, *Lin(nodal)* and *PC_1(avg)*, overestimate disamenity costs and, consequently, lessen the expansion significantly more. The implementation with an average German disamenity cost distribution across all regions, *Lin(avg_DE)*, particularly harms expansion in the northeast and yields the lowest onshore wind power capacity (250 GW). Accordingly, the implementations with lower contributions from onshore wind power require a higher supply of H_2 imports in compensation, leading to additional system costs of up to 2 bn. EUR.[5]

Figure 9 depicts the distribution based on the region's capacity potential utilization. For low disamenity, all implementations show a slightly lower median than the cost-optimal solution and shift the maximum density away from full capacity potential utilization. Furthermore, avoiding average data (as in *Lin(avg_DE)* and *PC_1(avg)*) lowers the upper quartile. Applying high disamenity results in more pronounced distribution patterns. The implementations *Lin(nodal)*, *PC_5*, and *PC_20* have similar minimums, maximums, and averages. In comparison, the implementation with a homogeneous disamenity cost distribution, *Lin(avg_DE)*, provides a more condensed distribution (highest minimum and lowest maximum). In contrast, constant marginal disamenity cost functions (such as the cost-optimal solution and *PC_1(avg)*) produce extreme dispersion between regions.

Efficacy

The purpose of considering disamenity costs in energy system optimization is to establish designs with better social acceptance, in this case, through reduced exposure of the human population to wind turbines. As in Section "Trade-offs between objectives", we use each implementation's regional expansion results and calculate the effective disamenity costs based on the original disamenity cost function (cf. Equation 2). Finally, we determine the average disamenity costs for all utilized turbine sites, accounting for different expansion levels (cf. Figure 10). For the scenario of low disamenity valuation, which provides similar results to the cost-optimal solution, the implementations *Lin(nodal)* and *PC_5* can equally yield a reduction of disamenity costs by 22% compared to the benchmark (*PC_20*). Using an average (*Lin(avg_DE)*, *PC_1(avg)*) still allows the realization of a reduction between 8% and 10%. For a high disamenity valuation, any implementation except *PC_1(avg)* more than halves the disamenity costs compared to the cost-optimal solution (-53%). However, this cannot be reached simply by reallocating turbines but rather requires reduced installed capacity for higher flexibility (cf. Figure 8). The constant marginal disamenity cost function of the *PC_1(avg)* implementation can realize only parts of the reduction potential: it comes with an increase of 29% in effective disamenity costs per turbine, with even fewer erected turbines (in total -42 GW).

[5] For reference, depending on the implementation, the total model-endogenous disamenity costs amount to 1.3 to 1.6 bn. EUR for the lower valuation and 5.1 to 7.0 bn. EUR for the upper valuation, respectively.

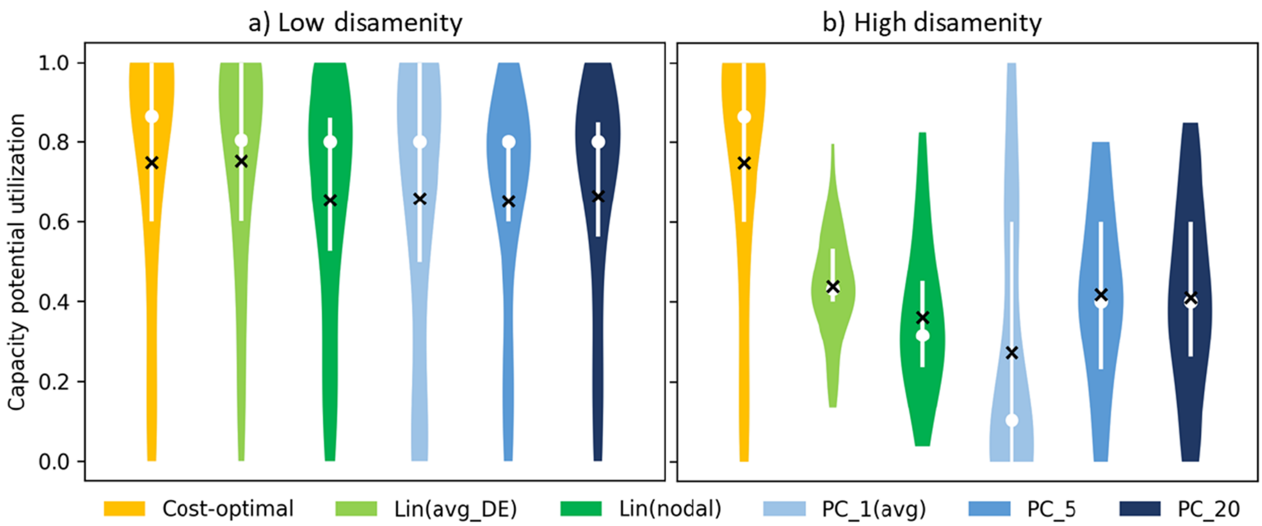

Fig. 9 Capacity potential utilization distribution of onshore wind power among all model regions by the implementation for the disamenity data scenarios (**a**) 'Low' and (**b**) 'High' showing minimum, maximum, quartiles and median (white), mean (black), and density. It should be noted that the mean of the distribution is not equivalent to the global capacity potential utilization due to the heterogeneity of the model regions

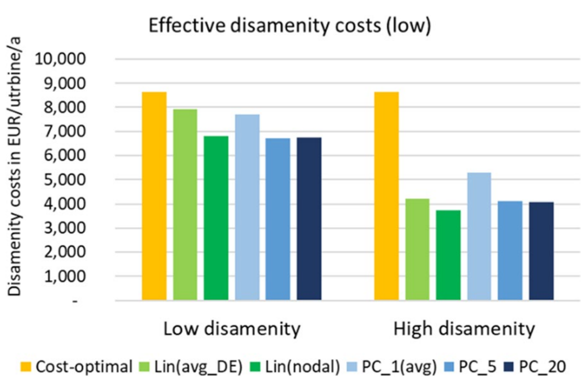

Fig. 10 Effective specific disamenity costs of each implementation for the disamenity data scenarios 'Low' and 'High'. We normalized both to the low disamenity data scenario for comparability (*y*-axis)

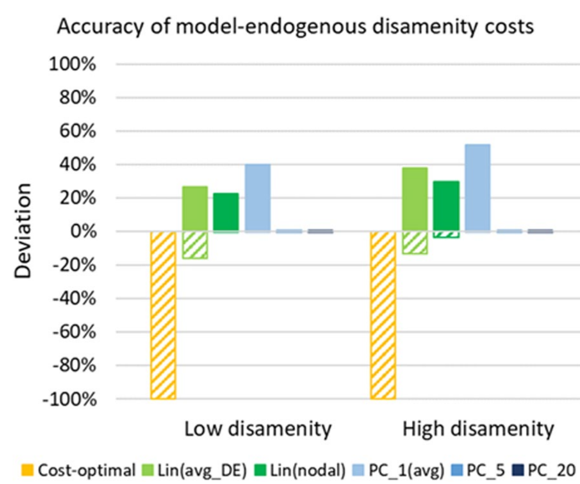

Fig. 11 Aggregated deviation of regional model-endogenous from effective disamenity costs by the implementation for the disamenity data scenarios 'Low' and 'High'

Accuracy

To determine the accuracy of the implementations, we use the model-endogenous disamenity costs, resulting from Eqs. 6, 7, and 10 (depending on the implementation), and compare them with the effective regional disamenity costs based on Eq. 2 as the benchmark. Furthermore, we separate positive and negative deviations and relate them to the aggregated effective disamenity costs of the solution; for example, the cost-optimal solution underestimates the disamenity entirely (cf. Figure 11). As the majority of marginal disamenity cost functions are increasingly growing (cf. Figure A.4 in the Appendix), most parts of the linear approximation *Lin(nodal)*, with its constant slope, lie above this curve and overestimate the disamenity costs in the model (23–30%). For the *Lin(avg_DE)* implementations, this still holds on average, whereas the average constant disamenity costs (*PC_1(avg)*) show even higher positive deviation (40–52%), which typically grows further if less of the onshore wind power potential is utilized.

The piecewise-constant implementations *PC_5* and *PC_20* are both very accurate, with deviations smaller than 0.5%; however, they do not provide the same results. As each region's marginal cost function is a step function, it is often optimal to utilize an interval entirely, where the approximations equal the original cost function. Therefore, in many cases, a region's capacity potential utilization becomes a multiple of $1/I$, with I being the number of intervals. Consequently, using more intervals increases the granularity of the capacity potential utilization

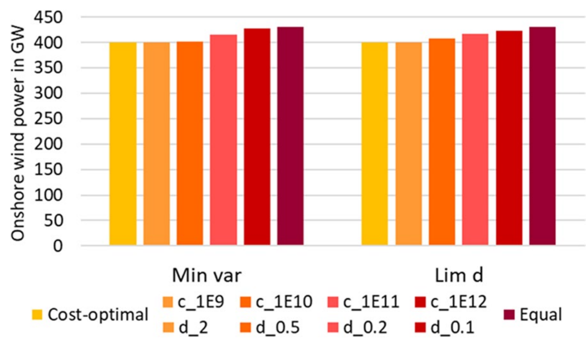

Fig. 12 Total installed capacity of onshore wind power by selected parameter values for the two equality modeling approaches *Min var* (upper parameter row) and *Lim d* (lower parameter row)

variable. Due to the already high accuracy, we omitted an analysis of piecewise-linear disamenity cost functions, which could fit the original curves continuously.

Implementation comparison: Equality

In the following, we compare the two model approaches (cf. Table 2 in Sect. "Implementations") that account for the equality of onshore wind power distribution in the energy system optimization process. To do so, we apply a parameter variation for each approach and demonstrate the approaches´ influence on the onshore wind power model results. Furthermore, we discuss the efficacy and the inclusion of equality as a criterion in existing distribution decisions in Germany.

Onshore wind power expansion and distribution

Figure 12 depicts the total installed capacity of onshore wind power for the two implemented approaches, which consider equality in the modeling process of energy system optimization models. Both approaches interpolate between the two extremes: the cost-optimal and the equally distributed solutions. However, the four selected parameter values for each approach—the weight in the co-optimization $c^{eq} \in \{10^9, 10^{10}, 10^{11}, 10^{12}\}$ and the constraining maximum deviation parameter $d \in \{0.1, 0.2, 0.5, 2\}$—cannot be compared directly across the two approaches. Both approaches share the trend of more installed onshore wind power capacity to compensate for the less efficient allocation at increasing levels of equality (in total, 30 GW between the extreme solutions).

Figure 13 reveals the different mechanisms of the two approaches. Minimizing the variance of regional capacity potential utilization (*Min var*) penalizes outliers and, thus, the strong exploitation of the best wind sites. The approach incentivizes the use of more disadvantageous sites, which are not used in the cost-optimal solution, for example, as their use reduces the costs of inequality and compensates for the lower energy supply of good sites while maintaining the global capacity potential utilization at a higher level. Applying the quadratic objective function leads to a concentration of capacity potential utilization values close to the global capacity potential utilization. In contrast, deploying constraints to limit the spread of regional capacity potential utilization (*Lim d*) enforces a smaller solution space and, consequently, avoids outliers. This approach produces a different distribution pattern, as the regional capacity potential utilization values concentrate at the lower and upper bounds. As the quartiles indicate, allowing a deviation of 50% ('d_0.5') from the average causes more than half of the regions to be equal to the lower or upper bound.

Efficacy

To assess the efficacy of both implementations, we illustrate the trade-off between more equally distributed onshore wind power turbines and additional system costs for the two approaches in Fig. 14. For the *Lim d* implementation to reduce the RSD by one-third, a maximum deviation of 50% from the mean ('d_0.5') is necessary but comes with an additional 0.5 bn. EUR in system costs. Minimizing the variance (*Min var*) results in a Pareto front, requiring additional system costs five times lower than those required for the same decrease in RSD.

Given the relatively low absolute difference in total system costs between the cost-optimal and equal solutions, as well as the questionability of the inequality measure itself, the differences may be negligible. However, we found a remarkably high correlation (>0.99) between the RSD and the Gini coefficient [45], which is the predominant inequality measure used to assess spatial distribution across the literature on energy system analysis [11]. As the Gini coefficient presents challenges regarding integration into optimization models, minimizing the variance and the associated RSD may offer a viable alternative for co-optimizing equality.

Accuracy

We applied the RSD to measure the degree of equality, which itself, is only a proxy for a just distribution of onshore wind power. This impreciseness complicates the assessment of how accurately the presented model approaches serve their purpose. As an alternative, we analyze how the criterion of equality has been integrated into the planning processes for the future distribution of onshore wind power in Germany. Based on the act on the determination of area requirements for onshore wind energy [46], the federal states must designate a percentage of their area for wind turbines and must provide realization plans. Figure 15 provides an overview of how the federal states plan to utilize the land area of their subordinate planning regions for onshore wind power [47].

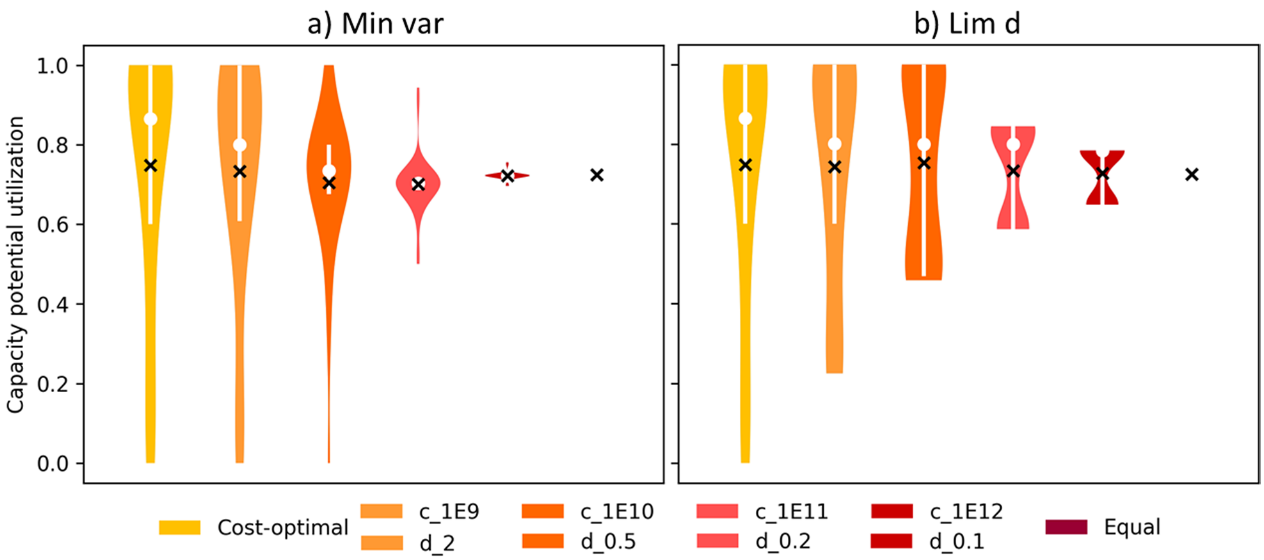

Fig. 13 Capacity potential utilization distribution of onshore wind power among all model regions by selected parameter values for the two equality modeling approaches a) *Min var* (upper parameter row) and b) *Lim d* (lower parameter row) showing minimum, maximum, quartiles and median (white), mean (black), and density. Note that the mean of the distribution is not equivalent to the global capacity potential utilization due to the heterogeneity of the model regions

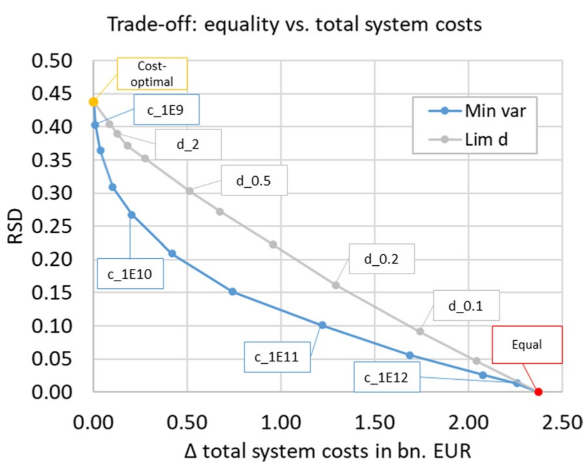

Fig. 14 Illustration of trade-offs between a cost-optimal and an equally distributed onshore wind power by the model approach using the relative standard deviation and additional total system costs as criteria

Based on land area, equality is the predominant distribution criterion, in contrast to the current distribution of onshore wind power [48]. Seven federal states distribute wind turbines entirely equally among their planning regions. North Rhine-Westphalia and Saxony-Anhalt also use equality as the primary decision criterion, making exceptions for two densely populated areas (limited to 75% of their capacity potential) and a scenic and touristic region, respectively. This procedure also applies to the distribution among Germany's federal states, which must provide between 1.8% and 2.2% of their land area (RSD of 0.1) when the city-states are excluded. Lower Saxony, with its small, heterogeneous planning regions, and Thuringia use multiple criteria that involve a capacity potential study and existing installations.

Nonetheless, in contrast to energy system analysis, land area is a preferred and reliable control indicator in practice. Furthermore, it is noteworthy that wind conditions are scarcely mentioned as a decision criterion. Policymakers may tend to favor simple decision rules, as they present fewer obstacles in the implementation process. This could be an argument in favor of more straightforward modeling approaches, such as limiting the deviation of capacity potential utilization. However, a resemblance to existing decision-making rules does not necessarily imply that a rule will provide a better solution [49].

Performance

As computational resources are scarce, a relevant factor for the choice of an implementation is its impact on the computational performance. To provide more robust results, we increased the samples. We used different scenario setups, including the variation of H_2 import prices (90 and 60 EUR/MWh), disamenity cost scenarios ('Low' and 'High'), and parameter values for the equality implementations. Given the similar size of the models, the reading time[6] for all samples and implementations did not differ consistently (all models in the interval between

[6] The time it takes to process the input data and set up the optimization problem.

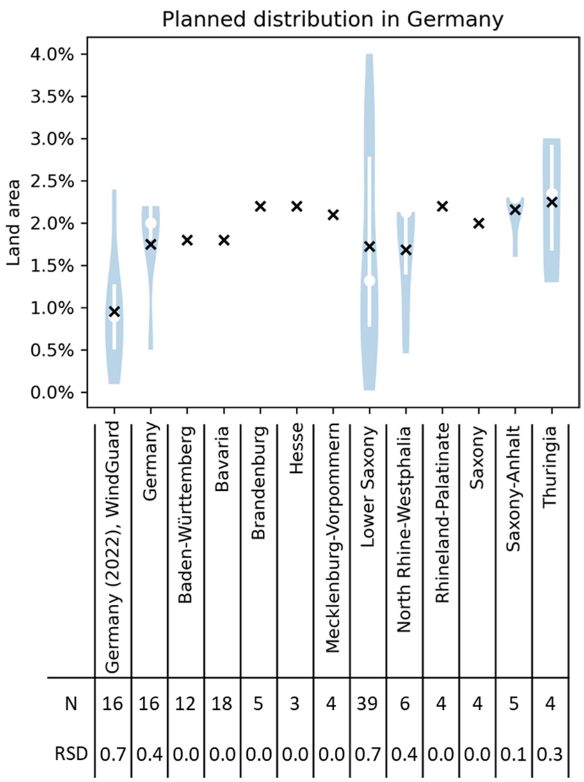

Fig. 15 Plans of onshore wind power distribution per land area in Germany and subordinate planning regions in 2032. The plots include the minimum, maximum, quartiles and median (white), mean (black), and density (blue), as well as information about the number of planning regions N and the relative standard deviation (RSD) of the distribution. Non-listed federal states have not yet provided plans

1786 s and 1911 s). Therefore, Fig. 16 displays the solving time of all samples for each implementation of the two social aspects of disamenity costs and equality. We conducted all optimizations using an Intel Skylake Xeon Gold 6130 with 96 GB of RAM.

The cost-optimal solution is solved the fastest on average. However, all LP implementations of disamenity costs show similar solving times, mainly between 10,000 s and 13,000 s. The QP implementations *Lin(avg_DE)* and *Lin(nodal)* take approximately 60–115% more time to solve. The observations for the inclusion of equality are similar: implementing additional linear constraints, which allow only a given deviation of capacity potential utilization, increases the solution time between 2% and 20%. We see the tendency that limiting the solution space increments the solving time, as the samples with equal distributions take the longest time to solve. For the QP model approaches for disamenity costs, minimizing the variance requires more time than for the alternative LP models (+50–115% compared to the cost-optimal solution). In addition, we observe increasing numerical instability for high weights due to the high coefficient c^{eq} and the small power of the capacity potential utilization $\gamma_k \in [0, 1]$. However, the presented implementations may still be advantageous, despite the higher effort they require, if other modeling techniques involving multiple model runs can be avoided.

Discussion

Recommendations

This section is devoted to energy system modeling and may serve as a guide for the integration of disamenity

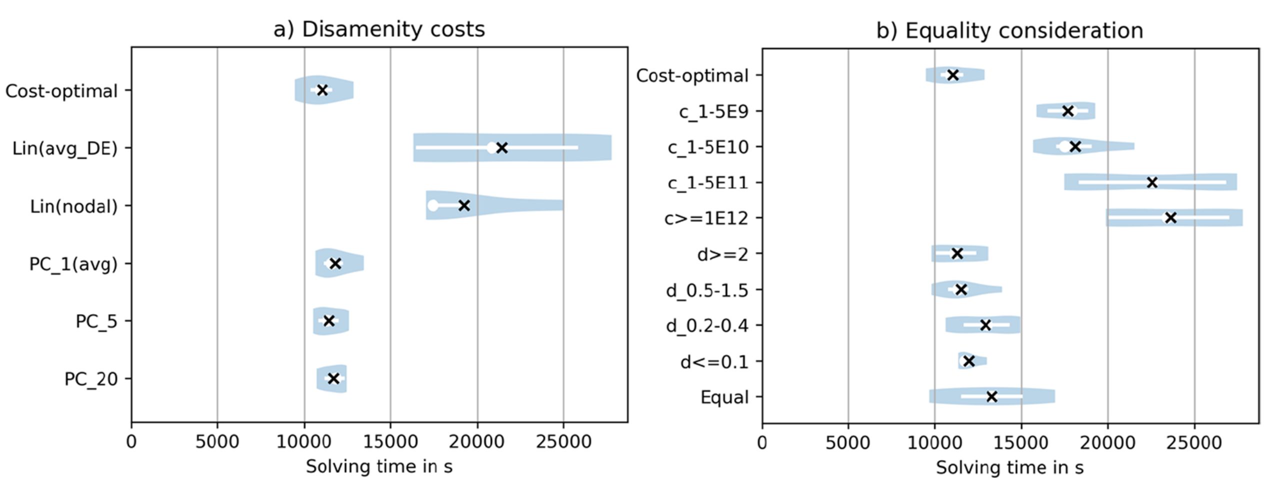

Fig. 16 Solving time of different samples for (**a**) disamenity costs and (**b**) equality implementations. The plots include the minimum, maximum, quartiles and median (white), mean (black), and density (blue). For the equality implementations, we grouped parameter ranges: e.g., 'c_1-5E9' includes values for the weight $c^{eq} \in \{1 \cdot 10^9, 2 \cdot 10^9, 5 \cdot 10^9\}$ and 'd_0.5–1.5' contains values for the maximum deviation $d \in \{0.5, 1, 1.5\}$

Table 3 Summary of the evaluation of the different implementations for disamenity costs and equality

	Implementation	Objective function	Efficacy	Accuracy	Model complexity	Parametrization	Performance
Disamenity costs	Lin(avg_DE)	QP	+	–	+	+	–
	Lin(nodal)	QP	+	o	+	o	–
	PC_1(avg)	LP	o	–	+	o	+
	PC_5	LP	+ +	+ +	–	–	+
	PC_20	LP	+ +	+ +	–	–	+
Equality	Min var	QP	+ +	+	o	–	–
	Lim d	LP	+	+ +	o	+	+

We evaluate the implementations with '+' as positive, 'o' as intermediate, and '–' as negative

costs and equality into energy system optimization models. Table 3 provides an overview of all implementations and an evaluation by the authors based on the results from Sects. "Implementation comparison: Disamenity costs" and "Implementation comparison: Equality", the model requirements from Sects. "Disamenity costs" and "Equality", and the performance (Sect. "Performance"). As is generally applicable in the realm of modeling, we recommend striving for high efficacy and accuracy while ensuring alignment with other modeling demands, such as available data and resources. Consequently, the implementation choice of the model feature may depend on the circumstances, particularly its importance for the research question.

Regarding the integration of disamenity costs, all implementations effectively reduce disamenity. However, constant average marginal disamenity costs, *PC_1(avg)*, should be avoided. An interpolation with five equidistant cost levels (*PC_5*) generally suffices to approximate the original cost function. If data for the parametrization is sparse, linear approximations can serve as an alternative. Despite the additional effort needed to solve the quadratic models, computational resources should not hinder the integration of disamenity costs because the additional solving times of the LP implementations are only incremental. For the parametrization of disamenity costs, it should be noted that the data is always bound to the underlying potential data. The low setback distances in this study lead to relatively high potentials with high marginal disamenity costs. Despite this, the low valuation of disamenity costs has no impact on the expansion of onshore wind power and only a small impact on the distribution and seems to underestimate its historically observed effect [17]. The scenario with a high disamenity valuation comes with an acceptable trade-off, while mitigating the exposure of the human population, and may be suitable for incorporating the effect of disamenities caused by wind turbines. However, quantifying disamenity costs for the status quo is already challenging due to varying individual preferences and the need for political judgment regarding the relative importance of these costs compared to other objectives. For example, the valuation of disamenity by Lehmann et al. [16] is roughly an order of magnitude higher than that by Ruhnau et al. [15]. Furthermore, these costs can change over time and may be influenced by decision-makers, such as through community participation or compensation [50, 51].

Both implementations that consider equality in the optimization model can be applied; however, they have different strengths: minimizing the variance of the region's capacity potential utilizations reduces inequality more effectively but comes with higher computational requirements. In contrast, adding linear constraints to limit the deviation between regions involves little additional effort and more closely resembles the existing distribution plans in Germany. The increased transparency of simple measures may contribute to improving perceived procedural justice and, thus, establish a more accepted result. Regarding the parametrization for Germany, we find equality to be the predominant distribution criterion for future distributions, which should also be recognized in techno-economic modeling. First, every planning region must contribute and dedicate some parts of its land area to onshore wind power. Second, the RSD of the observed distributions is typically 0.3 or lower if exceptions are considered, such as in highly populated urban areas, which also occurs due to the land area metric applied in politics, in contrast to the potential data used in energy system modeling. To reduce the RSD in this study to 0.3, the weight c^{eq} for the minimized variance must be in the magnitude of $5{\cdot}10^{9}$ EUR. Alternatively, the maximum deviation parameter d for the LP implementation should be 50% or lower. The value for the weight c^{eq} may be less intuitive, as it depends on the remaining objective function and can vary case by case. In contrast, the maximum deviation parameter's connotation is relatively simple and is mathematically advantageous (generally, d > RSD and for a small maximum deviation,$d \approx$ RSD).

Limitations

This study has limitations that should be taken into consideration when interpreting the presented results. While we focused on the social acceptance of onshore wind power distribution and expansion, we analyzed the impact of the two considered aspects, disamenity costs and equality, individually. In practice, these aspects have interdependencies and collectively contribute to community and socio-political acceptance [13, 52].

In general, disamenity costs are characterized by uncertainty, given their dependence on individual attitudes, which can evolve over time and may be positively influenced by factors such as participation. The disamenity costs applied in this study follow a relatively narrow definition based on the proximity of human settlement but, for example, do not consider spatially heterogeneous landscape aesthetics.

Regarding equality, the capability-oriented approach underscores the heterogeneity of the model regions' potential, potentially resulting in unequal effects on individuals both between and within regions. In addition, we omitted the consideration of environmental impact as another external effect of onshore wind power expansion.

Furthermore, our focus on a single country, Germany, limits the generalizability of our findings in two ways. First, other countries have diverse characteristics, such as population distribution [15], and may prioritize criteria differently [17]. Second, energy system analysis may involve broader geographical coverage, including multinational scenarios with greater regional differences in wind resources, energy policies, and social norms. These differences complicate the search for common ground in social objectives and, consequently, parametrization, which suggests that a more flexible and relaxed modeling approach may be required.

Ultimately, we examined only one scenario, a climate-neutral Germany with other fixed renewable energy sources and demands, taking a greenfield approach that does not consider transition inertia or build-up limits. In addition to underestimating additional externalities, the adoption of this scenario may be one reason the resulting aggregated installed capacity of onshore wind power in this study lies, for the most part, above that reported in other studies [53].

Conclusion

We studied how social aspects related to onshore wind power may be integrated into the optimization of energy systems to enhance model results for decision-makers. In comparison to established cost-optimal solutions and in the context of a climate-neutral Germany, we observed a relatively modest increase in total system costs. This increase amounts to up to 3% when incorporating disamenity costs and 2% when striving for an equal distribution based on available regional potential. Importantly, we found no indication that onshore wind power would cease to be an essential part of the renewable energy system. While the impact of these social factors on the expansion of onshore wind power is limited, the spatial distribution among the considered model regions was significantly altered.

Regarding model integration, we identified effective LP implementations for both social aspects with high accuracy, notably outperforming the tested QP implementations, which require longer solution times (+ 50–115%). By applying the upper-case scenario of the integrated data set of disamenity costs, we observed a substantial impact on the distribution of onshore wind power. This includes a reduction in disamenities by more than a half on average (-53%) and a reduction in the exposure of the human population to wind turbines, indicating the potential to identify more socially accepted distributions within energy system optimization models.

Our analysis of existing plans for Germany reveals that equality is a major driver in current policy-making for the distribution of onshore wind power. As an essential discipline in policy-making, welfare economics offers methods to assess the quality of distributions, and we recommend its inclusion in future spatially distributed energy system modeling. Consequently, limiting the dispersion in the distribution of onshore wind power helps achieve the objective of a just distribution but also aligns with the smaller practical solution space for decision-makers and, consequently, for energy system designs. Both our suggested approaches to incorporating equality enable modulation of the degree of equality in the spatial distribution, facilitating the involvement of stakeholders.

Furthermore, we recognize several future avenues for research to build upon our findings. First, there is a need to assess the methodological error inherent in energy system optimization models when utilizing regional aggregations of wind resources and disamenity cost curves compared to the precision offered by spatially explicit turbine placement models. Second, a holistic co-optimization of technologies, including the expansion and distribution of PV and transmission grids, is desirable. However, this co-optimization would require an exhaustive assessment of the externalities associated with onshore wind power, encompassing factors such as environmental considerations, as well as a careful equilibrium with the externalities linked to alternative technologies. Finally, in social science, researchers should strive to

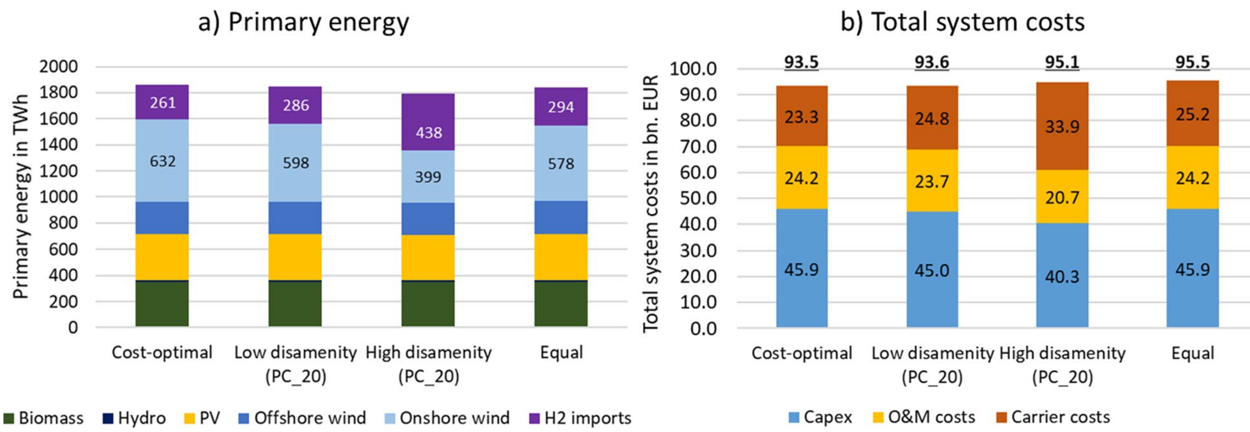

Fig. 17 Comparisons of (**a**) primary energy and (**b**) total system costs for including the suggested social aspects of disamenity costs and equality with an H_2 import price of 60 EUR/MWh

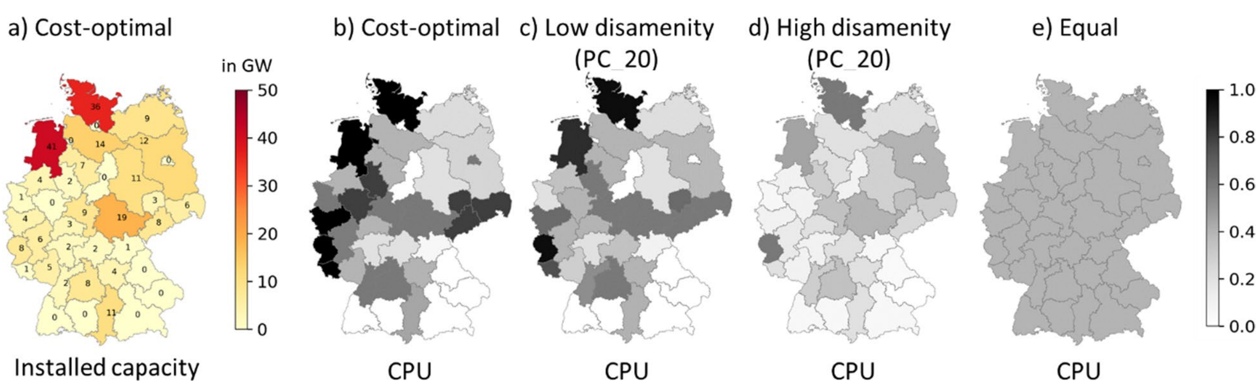

Fig. 18 Spatial distribution of onshore wind power by (**a**) installed capacity of the cost-optimal solution and by (**b–e**) the capacity potential utilization (CPU) of the highlighted solutions with an H_2 import price of 60 EUR/MWh

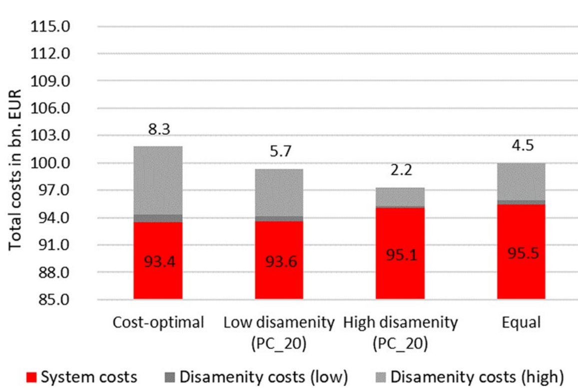

Fig. 19 Comparisons of the total costs for the four highlighted solutions with an H_2 import price of 60 EUR/MWh. The total costs consist of system costs (red) and projected disamenity costs of onshore wind power (gray) for the data scenarios 'Low' and 'High'

identify the key characteristics of socially optimal energy systems that are subject to the results of energy system optimization models.

Appendix

See Figs. 17, 18, 19 and 20.

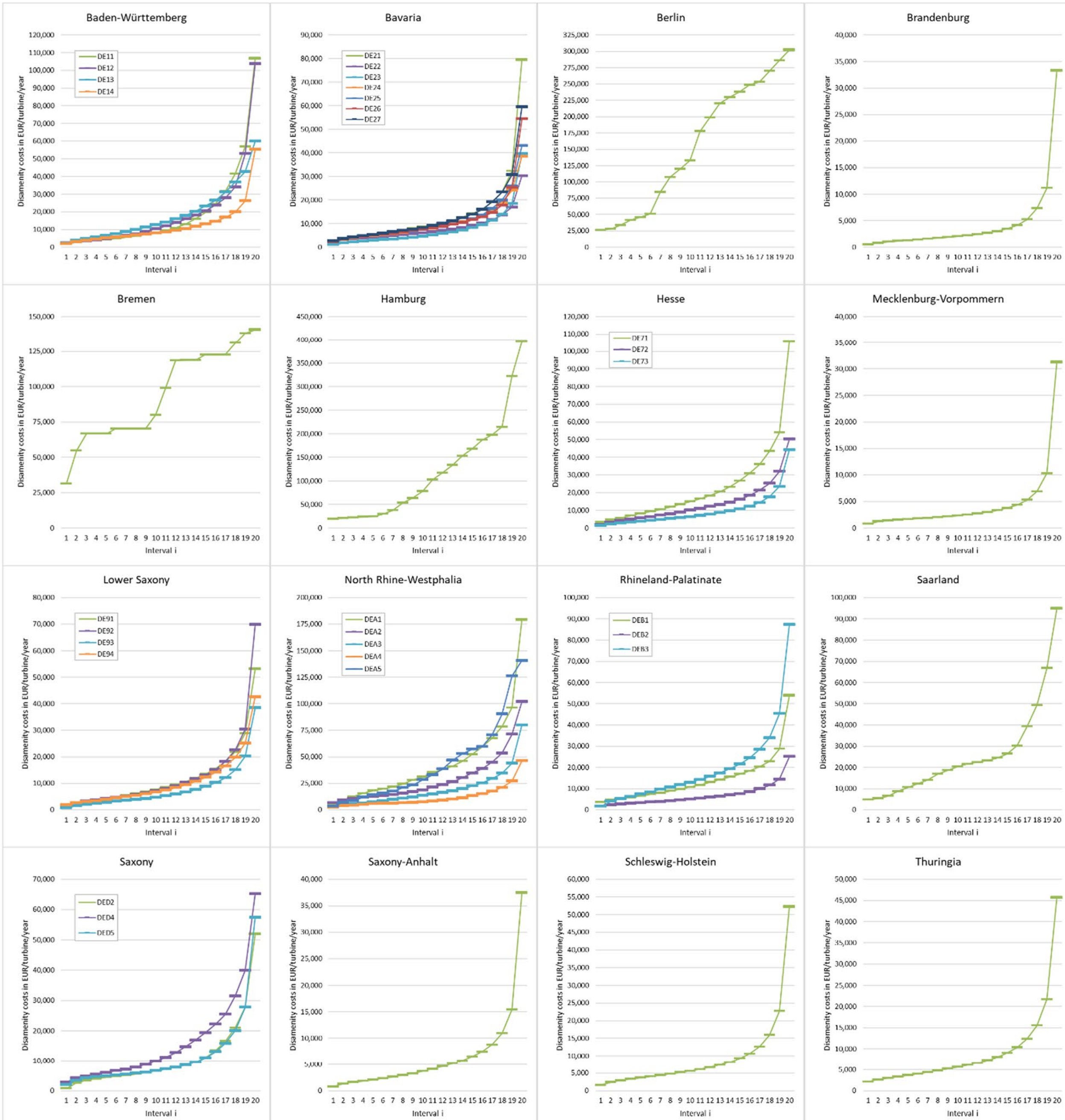

Fig. 20 Marginal disamenity costs per turbine (lower-case) of the 38 model regions clustered by federal-state and divided into 20 intervals

Abbreviations

Capex	Capital expenditure
CPU	Capacity potential utilization
ESTRAM	Energy system transformation model
H_2	Hydrogen
LP	Linear problem
NUTS	Nomenclature of territorial units for statistics
O&M	Operation and maintenance
PV	Photovoltaic
QP	Quadratic problem
RSD	Relative standard deviation

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Author contributions

C.L. conceptualized the study and developed its methodology. C.L., F.P., and M.S. developed the software. R.N. and A.B. administered the project. A.B. and R.H. supervised the work. C.L. prepared the original draft and its visualizations. F.P., M.S., A.B., R.N., R.B., and R.H. reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
The data sets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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