SENSITIVITY ANALYSIS OF THE ENERGY TRANSITION PATH IN THE BERLIN-BRANDENBURG AREA TO UNCERTAINTIES IN OPERATIONAL AND INVESTMENT COSTS OF DIVERSE ENERGY PRODUCTION TECHNOLOGIES

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ABSTRACT

The investigation of energy transition paths toward a sustainable and decarbonized future under uncertainty is a critical aspect of contemporary energy planning and policy development. There are numerous methods for analysing uncertainties and sensitivities and many studies on sustainable transformation paths, but there is a lack of combined application to relevant use-cases. In this study, we investigate the sensitivity of energy transition paths to uncertainties in operational and investment costs of power plants in the metropolitan area of Berlin and its rural surroundings. By employing the linear programming energy system model oemof-B3, we extensively focus on the system's energy technologies, such as wind turbines, photovoltaics, hydro and combustion plants, and energy storages. Greenhouse gas reduction and electrification rates per commodity are realized by selected constraints.

Our research aims to discern how investments in energy production capacities are influenced by uncertainties of other energy technologies' investment and operational costs in the system. We apply a quantitative approach to investigate such interdependencies of cost variations and their impact on long-term energy planning. Thus, the analysis sheds light on the robustness of energy transition paths in the face of these uncertainties.

The region Berlin-Brandenburg serves as a case study and thus reflects on the present space conflicts to meet energy demands in urban and suburban areas and their rural surroundings. An electricity-intensive scenario is selected that assumes a 100 % reduction in greenhouse gas emissions by 2050. With the results of the case study, we show how our approach enables rural and metropolitan decision-makers to collaborate in achieving sustainable energy.

Decision-making in long-term energy planning can be made more robust and flexible by acknowledging the identified sensitivities and enable such regions better to navigate challenges and uncertainties associated with sustainable energy planning.

1. INTRODUCTION AND STATE-OF-THE-ART

Examining energy transition paths for a sustainable and decarbonized future amid uncertainty is a crucial aspect of modern energy planning and policy development. Investment costs and projected operational costs play a significant role in shaping decisions regarding transition pathways once an energy system is in place. Energy system optimization models (ESOMs) are useful tools to study transition pathways and analyze robust decisions. They are technology-rich optimization models covering an entire energy system, typically aiming to minimize the total system costs (or for some purposes socio-or techno-economic cost

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parameters). However, these costs come with considerable uncertainties. If not appropriately considered, translated into the real world with uncertain and non-deterministic parameters, these uncertainties can erode trust in planning based on ESOMs.

One most commonly employed strategies to tackle this challenge is parametric sensitivity analysis, achieved by perturbing input parameters and handling uncertainties by using scenarios (Yue et al., 2018). This approach often involves solving numerous scenarios, demanding substantial computational effort. Based on these computations one can retrieve the most reliable investment decisions, which are those that exhibit the least sensitivity to the uncertainties considered. Nevertheless, sensitivity analysis in linear programming can sometimes eliminate the need to re-solve the problem, when a parameter changes. Instead, knowledge gained from sensitivity analysis allows analysts to deduce how changes in a linear programming parameter impact its optimal solution based on the original solution.

Each model parameter comes with uncertainty and a distinct role in influencing the modeling result in interaction with the remaining model parameters. Computationally expensive global sensitivity analysis can provide a comprehensive understanding of the model's behavior by considering all model input parameters (Ginocchi et al., 2021). It enables identifying which parameters are most influential in driving model output, while some of those are out of control by decision-makers and can be considered with rigorous scenario development. In practice, the analysis of selected scenarios is a standard method for considering uncertainties in energy system analysis (Child et al., 2018). However, scenario analysis' limited coverage of the parameter space contain the risk of potentially overlooking important insights. The analysis in this paper exemplifies the added insights of a local sensitivity analysis in a one-parameter-at-a-time approach and centers on the technological cost parameters of the model.

This paper contributes to energy system analysis under uncertainties, focusing on a case study in the Berlin-Brandenburg area. We utilize the open-source energy system model oemof-B3 to examine the electricity and heat sectors. Our analysis explores sensitivities to uncertainties in operational and investment costs, particularly in a scenario that emphasizes high electrification levels. By employing LP sensitivity analysis, we aim to make more efficient use of computational resources. In the following sections, we introduce the case study and scenario, conduct sensitivity analysis, and present computational results to draw conclusions on system robustness.

2. CASE STUDY AND SCENARIO

The case study models Germany's federal states Berlin and Brandenburg. These federal states are characterized by a metropolitan area with high energy demand and low land availability and rural areas with comparatively lower energy demand per area but higher land availability. The urban-rural divide in the supply and consumption of energy harbors potential for conflict in terms of environmental pollution and economic participation through energy production.

Energy demands in regions with such spatial and settlement structure conditions are often largely covered by rural areas due to natural-topographical constraints. The growing demand for energy reinforces this development and leads to an increasing need for planning, involving urban and rural stakeholders, in order to enable and maintain a just energy transition. Thus, this case study insights can serve as a benchmark for regions with similar settlement structures and natural-topographical characteristics.

2.1. Model and Reference Energy System

The open-source energy system model oemof-B3 is used to simulate and optimize the energy system. The model is based on various libraries of the open source framework oemof (community, 2023): The model generator oemof.solph (Krien, Schönfeldt, et al., 2020; Krien, Kaldemeyer, et al., n.d.), oemoflex (Launer, Meier, et al., 2023) for the preparation of data packages and oemof.tabular (Simon Hilpert, 2021; @jnnr et al., 2023).

The oemof-B3 model minimizes the total system costs of the energy system under several boundary conditions. All boundary conditions and the objective function are linear for simplification. For the future

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development of final energy demand, prices, and emission factors are assumed to be perfect foresight for optimization. The sector-coupled energy model covers the electricity and heat sector. Figure 1 shows a schematic representation of the reference energy system and its components.

Various conversion technologies mediate between the energy sources electricity, heat, hydrogen, and methane. In the case of heat, centralized heat and decentralized heat are treated separately via heating networks and decentralized generation. Electricity generation from renewable energies (wind, pv, run-of-river power plants) is shown as one source of electricity per technology, for which hourly weather time series are used. Gas-fired power plants are implemented as conversion technologies that convert gas into electricity (gas turbine), heat (boiler), or both (combined heat and power). Electricity-driven conversion technologies such as heat pumps (centralized large-scale heat pumps or decentralized household heat pumps), electrolyzers and resistance heaters connect the electricity sector with the heat and hydrogen sector. Furthermore, storage facilities are implemented for various energy sources (H2-cavern, central and decentral heat storage).

The model assumes both German federal states as single nodes with interconnecting electricity lines but with no additional connection to either another German federal state or Poland. The energy conversion technologies and their installed capacities are aggregated by the federal states.

The model determines the cost-optimized expansion and operation for the overall system, in a greenfield approach. The total minimized system costs include the variable costs for operation and maintenance, fixed costs for costs for operation and maintenance, and the annuitized investment costs of the individual components.

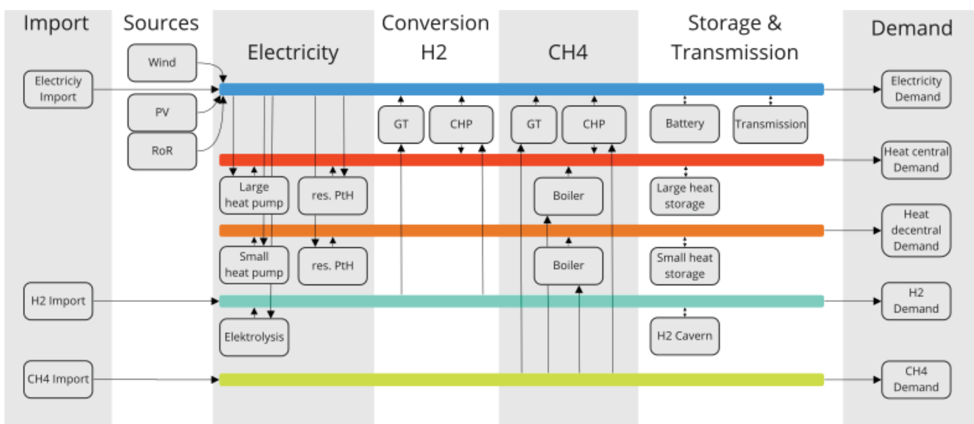

Figure 1: Reference energy system of case-study: The model shows imports and sources of renewable energy (left), the various technologies for energy conversion, storage and transmission (center) and the individual energy demands (right). The colored bars represent the balance areas of the energy sources or the substances electricity, heat - centralized, heat - decentralized, hydrogen, and methane.

2.2. Scenario

The scenario assumes a high degree of electrification and considers the electricity and heating sectors and hydrogen and methan, on the demand side, households, commercial, transport, and industry in 2050. The ratio of electricity to gas is included in the model as a boundary condition and is determined for both centralized and decentralized heat supply. Figure 1 shows which technologies can meet the corresponding demand. With regards to renewable technologies wind-onshore, solar-pv and hydro-ror fixed feed-in time series based on meteorological data are in place. By 2050 the emissions are limited to zero, in line with the goals of the German government to become carbon neutral. Capacity expansion limits are in place that restrict model deployment of wind and solar capacities due to geographical and settlement structures'

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Table 1: Techno-economic parameters

Technology	Capacity cost	Capacity cost_unit	OPEX (% of invest)	Lifetime (a)	Efficiency	References	State
wind-onshore	1190000	EUR/MW	1.14%	40		(Agency, 2016)	all
solar-pv-roof	849900	EUR/MW	1.16%	45		(Agency, 2016)	B
solar-pv-ground	458442	EUR/MW	1.82%	45		(Agency, 2016)	BB
hydro-ror	4000000	EUR/MW	2.00%	80	0.9	(DIW, 2013)	all
ch4-gt	850000	EUR/MW	2.35%	30	0.42	(Agency, 2016)	all
ch4-bpchp	1600000	EUR/MW	1.88%	30	0.55	(Agency, 2016)	all
h2-gt	535000	EUR/MW	3.74%	30	0.43	own assumption	all
h2-bpchp	1600000	EUR/MW	1.88%	30	0.43	own assumption	all
liion_battery	250000	EUR/MW	0.22%	45	0.94	(Agency, 2018)	all
	975000	EUR/MWh	0.50%				
ch4-boiler_large	250000	EUR/MW	1.00%	25	1.05	(Agency, 2016)	all
ch4-boiler_small	287857	EUR/MW	5.09%	18	1.02	(Agency, 2016)	all
electricity-heatpump_large	950000	EUR/MW	0.53%	40	5.7	(Agency, 2016)	all
electricity-heatpump_small	1900000	EUR/MW	0.26%	40	variable	(Agency, 2016)	all
electricity-pth	170000	EUR/MW	0.59%	20	0.99	(Agency, 2016)	all
heat_central-storage		EUR/MW		50	0.99	(Gardian et al., 2021)	all
	8000	EUR/MWh	0.41%			(Agency, 2018)	
heat_decentral-storage		EUR/MW		50	1	(Gardian et al., 2021)	all
	130000	EUR/MWh	20.51%			(Agency, 2018)	
electricity-electrolyzer	875000	EUR/MW	5.00%	35	0.8	(Agency, 2017)	
h2-cavern	163000	EUR/MW	0.00%	100	0.99	(Agency, 2018)	all
	1800	EUR/MWh	1.33%				all

boundaries. For Berlin, the upper expansion limit for solar-pv accounts for 9GW, in Brandenburg for 77GW, and the for wind-onshore 0.012GW in Berlin and 34 GW in Brandenburg respectively. No capacity or activity limits for conventional energy technologies are in place. However, the decision regarding the coal phase-out is a determining factor for the future development of conventional power plants in Berlin and Brandenburg. The coal phase-out in Germany according to law will be completed by the end of 2038, thus those technologies are not considered in the scenario. The input dataset and to this article is published on Zenodo (Launer, Haas, et al., 2023).

3. SENSITIVITY ANALYSIS OF SCENARIO

In this study, we investigate the dependence of the optimal energy mix on the input cost parameters representing the investment costs and the marginal costs for the technologies and carriers considered for the two federal states. We employ LP sensitivity analysis to first analyze the sensitivity of the energy mix to the input cost parameters and then generate perturbed scenarios based on the LP sensitivity analysis results.

3.1. LP Sensitivity Analysis

The oemof-B3 model is used to model the reference energy system explained in Section 2. It minimizes the total cost of the system constituted by capital expenditure and operational expenditure. Changing the input cost parameters defined in the scenario only changes the objective function coefficients, alternating the search direction of the linear program (LP) solution algorithm. Therefore, we perturb each input cost parameter one at a time to perturb the LP objective function and find a feasible solution to the system that has a total cost in the neighborhood of the optimal solution to the base scenario. Here, the size of the perturbation per cost parameter that changes the optimal solution matters to understand the optimal LP solution's sensitivity on each input cost parameter.

First, by LP sensitivity analysis, we analyze the sensitivity of the optimal solution of the base scenario with respect to the input cost parameters. These are represented in objective function coefficients of the scenario instance. We use the optimality conditions of the LP to find lower and upper bounds for the input cost parameters, consistent with the same optimal solution to the instance, in case we change only a single objective function coefficient.

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However, this is not straightforward for the oemof-B3 model. The challenge lies in the computation of the objective function coefficients based on the input cost parameters. First, the input cost parameters are the net present value (NPV) of capital expenditure (CAPEX) and fixed operational maintenance costs. The objective function coefficients related to the CAPEX on the other hand, address the equal annual annuity (EAA) of the total investment and the fixed maintenance costs. Thus, we map the sensitivities of the objective function coefficients back to nominal investment costs based on the computation below:

$$c_{t,i,r} = C_{t,i,r} \cdot \frac{w \cdot (1+w)^n}{(1+w)^n - 1} + f_{t,i,r} \cdot n \tag{1}$$

where, $c_{t,i,r}$ is the objective function coefficient representing the cost of unit capacity investment to technology t for carrier i in the region r, $C_{t,i,r}$ is the NPV of the capital expenditure, $f_{t,i,r}$ is the annual fixed operational maintenance cost, w is the weighted average cost of capital, and n is the lifetime of the investment. In this study, we have Berlin and Brandenburg, the two federal states in Germany, as the two regions.

Secondly, some input cost parameters influence multiple objective function coefficients. Hence, before interpreting the analysis results, we evaluate whether changing a single cost input parameter affects more than one objective function coefficient. This is particularly important as some of the cost values are equal to each other for installing a facility in different federal states or some technology costs are correlated. Here, we use the 100% rule (Bradley et al., 1977), when changing a particular input cost parameter affects more than one objective function value, to make inferences on the range of the input cost parameter change that keeps the optimal solution intact. Accordingly, we computed the lower bounds (LB) and upper bounds (UB) of this range for each input cost parameter.

After performing this analysis, we eliminate any perturbations that do not change the optimal solution of the base scenario, reducing the computation time.

An immediate result of the above-explained LP sensitivity analysis is that we cannot guarantee the optimality of the base scenario solution for any meaningful change in the marginal cost parameters in the scenario defined in Section 2.2. The reason is, in the scenario, a single input cost parameter applies to all periods of each carrier, technology, and region. So, we cannot make any scenario reduction in terms of input cost parameters affecting the objective function coefficients associated with operational maintenance costs (OPEX). In this study, we also do not analyze the fixed operational maintenance costs based on their marginal effect on the total cost specific to the scenario that we analyze.

For input cost parameters affecting objective function coefficients associated with CAPEX, the sensitivities are presented in Figure 2. In the table, we present the LP sensitivity analysis results of each input cost parameter in terms of the lower bound and upper bound for the parameter's interval that guarantees the same optimal solution as the base scenario. The first interval gives the analysis result and the second interval is considered when applying perturbation. The latter is determined by considering the costs in terms of their estimated bounds during the analysis period. For example, the interval of unit capacity investment cost for CH4 using small boiler technology that guarantees the base scenario optimal solution is larger than the estimated investment cost. Therefore, the optimal solution is practically insensitive to the changes in this input cost parameter and we deduct the scenarios involving its perturbations from our scenario set. Such cases are presented by "NONE" in the table. On the other hand, the optimal solution of the base scenario is insensitive to the changes in H2 cavern storage unit investment cost in Berlin as the LB and UB of the LP sensitivity analysis results are big numbers that we assume the interval is $(-\infty, \infty)$. However, because of the dependence of the costs in Berlin and Brandenburg for this carrier and technology pair, we cannot reduce the scenario set.

Consequently, in this scenario instance, by performing the LP sensitivity analysis, we reduce the number of input cost parameters to analyze from 15 to 13. We also cut the number of perturbations for three input cost parameters by half by considering the insensitivity of the optimal solution to increase or decrease in this cost parameter. Therefore, considering an equal number of scenarios generated by perturbing each cost parameter by both increasing and decreasing its value, the LP sensitivity analysis provided a

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23% immediate reduction in the scenario set regarding the objective function coefficients associated with CAPEX. The scenario reduction ratio would be even larger for the scenarios where the investment costs of the regions behave independently because of the differences between urban and suburban areas.

	Carrier	Technology	Region (Model)	Input Cost (LP		Region (Input)	Input Cost (Applied	
				LB	UB		LB	UB
Generators	ch4	boiler_large	B BB	0%	0%	ALL	0%	0%
		boiler_small	B BB	-60%	182%	ALL	NONE	NONE
	electricity	electrolyzer	B BB	0%	0%	ALL	0%	0%
		heatpump_large	B BB	0%	0%	ALL	0%	0%
		pth	B BB	-6%	INF	ALL	-6%	INF
	h2	cavern	B BB	-INF 0%	INF 0%	ALL	0%	0%
	h2/ch4	bpchp	B BB	0% 0%	INF 0%	ALL	0%	0%
		gt	B BB	0% 0%	INF 0%	ALL	0%	0%
	hydro	ror	B BB	-INF -INF	INF 42%	ALL	-INF	42%
	solar	pv	B BB	0% 0%	0% 0%	B BB	0% 0%	0% 0%
	wind	onshore	B BB	-INF 0%	0% 0%	ALL	NONE	0%
Storages	heat_central	storage	B BB	0%	0%	ALL	0%	0%
	heat_decentral	storage	B BB	-20%	5%	ALL	NONE	NONE
	electricity	liion_battery	B BB	0%	0%	ALL	0%	0%
	h2	cavern	B BB	-INF 0%	INF 0%	ALL	0%	0%

Figure 2: LP Sensitivity Analysis Results

3.2. Generation of Perturbed Scenarios

Based on the LP sensitivity analysis and anticipated technology costs, we set upper and lower bounds for input unit capacity and storage investment costs. Within these intervals, we selected discrete cost values to create our perturbed scenarios. On the other hand, we use the normal distribution to draw the amount of perturbations for the marginal costs for each variable. We set the input cost parameter itself as the mean value of the distribution and the standard deviation as $\frac{1}{3}$ of the marginal cost itself. With this setting, we have a non-negative marginal cost in the perturbed scenario which is greater than $\frac{1}{3}$ of the original cost about 99% of the time.

The overview of all scenario perturbations analyzed in this study is presented in Table 2. In this Table, the columns are partitioned according to the perturbed input cost types. The perturbed unit capacity investment costs and unit storage investment costs, denoted as "Capacity Costs" and "Storage Costs", respectively, are selected according to the LP sensitivity analysis results presented in Figure 2 and their expected values during the analysis period.

The results presented in the ensuing sections are distilled from the analysis of 446 scenarios in total generated based on the scenario in Section 2.2 by one-at-a-time perturbation of 296 input unit investment cost parameters, 80 input marginal cost parameters, and 70 input unit storage investment cost parameters.

We analyze the sensitivity of the energy transition path to the changes in the input costs. The lower and upper bounds and pertubations of the resulting installed capacity, OPEX, and CAPEX based on the scenario perturbations are shown in Table 2.

In the next section, we provide exemplary results using the plots from the dashboard and comment on the dashboard's utilization in decision-making under uncertainty.

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Table 2: Overview of Cost Perturbations (in EUR/MWh for marginal costs, EUR/MW for capacity and storage costs)

	Capacity Costs				Marginal Costs			Storage costs			
Technology	**lower bound**	**step size**	**upper bound**	**perturbations**	**lower bound**	**upper bound**	**perturbations**	**lower bound**	**step size**	**upper bound**	**perturbations**
boiler_large	9,920.25	10,000	219,999.14	30	-0.7	0.4	10				
electrolyzer	266,635.89	10,000	233,329.46	30							
heatpump_large	169,903.85	100,000	1,449,998.76	30	-0.8	1	10				
heatpump_small					-1.2	1.9	10				
liion_battery					-0.5	0.5	10	204,998.83	10,000	784,994.68	29
pth	36,253.52				-0.5	0.5	10				
bpchp	142,999.65	10,000	599,929.10		-3.9	1.6	10				
gt h2	149,994.79	10,000	379,999.68	30							
cavern h2	92,729.86	10,000	50,329.12	16	-0.5	0.5	10	200.00	50	599.90	12
central heat storage								799.02		5,199.99	29
ror		10,000	809,772.51	32							
pv	219,997.38	10,000	274,994.89	30							
wind onshore		10,000	309,998.66	30	sampled from normal distribution	0.5	10				

4. RESULTS ON THE EFFECT OF COST UNCERTAINTIES ON THE OPTIMAL ENERGY SYSTEM DESIGN

4.1. Base Solution of the Undisturbed Scenario

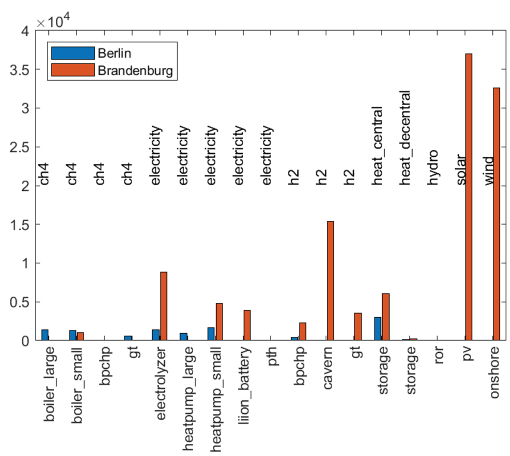

Figure 3: Base solution for undisturbed scenario (installed capacity in MW per technology and region). Installed capacities are depicted in blue for Berlin and in orange for Brandenburg.

Figure 3 shows that with the given investment cost from Table 1, the wind potential is almost fully invested in (region BB: 96%, region B: 100%). The solar-pv potential in the region Brandenburg is used to approx. 48% with 36995 MW, while the potential in Berlin is hardly used (approx. 0.5%). As there is mainly potential for rooftop systems in Berlin for reasons of space, the investment costs there are almost twice as high as in Brandenburg. In comparison, the transmission losses and costs for transporting electricity between the regions are relatively low. This is reflected in the high utilization of the transmission line of 85% (transport from Brandenburg to Berlin), while the solar-pv potential in the Berlin region remains almost unexploited. From a cost optimization perspective, the absolute values of the techno-economic parameters of wind turbines are less convenient than those of solar-pv: higher investment costs per MW, shorter lifetime, higher operating and maintenance costs, and marginal costs. The higher full load hours of wind turbines in of approx. 1700 hours (in BB) compared to those of solar-pv (approx. 1000 hours in BB/B) reduce this effect. Nevertheless, the wind potential is almost fully utilized, while only 48% of the solar-pv potential is used.

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4.2. Total Cost Sensitivity

First, we analyze the impact of the perturbations in Table 2 on the total cost. Hence, we investigated the impact of changing the unit capacity investment costs on the total OPEX and the effect of changing the marginal costs on the total CAPEX. These are presented in Figure 4a and Figure 4b, respectively. Capacity investment cost perturbations affect the resulting total OPEX within the interval of -60 to 30 million EUR while analysis of the plots shows that marginal cost perturbations influence the resulting total CAPEX within the range of ±1.5million EUR.

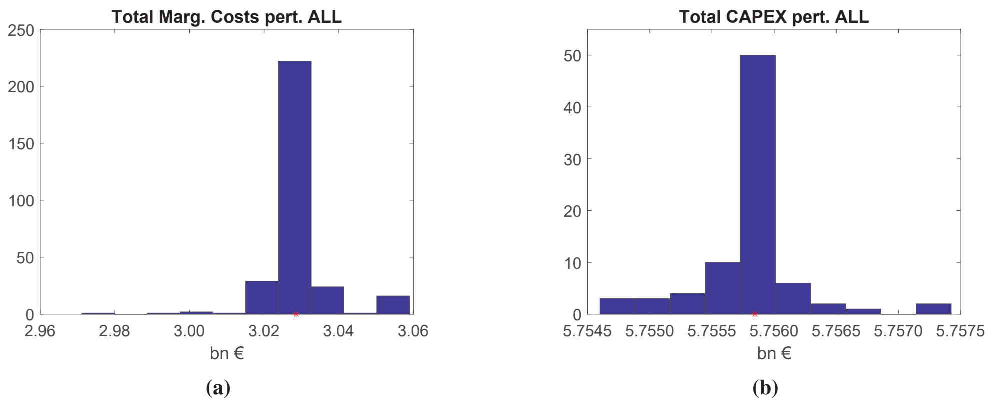

Figure 4: Histograms Illustrating the Effect of **(a)** Unit Capacity Cost Perturbations on Total OPEX **(b)** Marginal Cost Perturbations on Total CAPEX (Y axis representing the number of solutions in the interval of OPEX/CAPEX given in the X axis)

4.3. Capacity Sensitivity

Next, we investigate the sensitivity of the installed capacity to the changes in the capacity costs, storage costs, and marginal costs. The figures A.1, 5 and A.2 present the sensitivity of the installed capacity of the energy generators to the unit capacity investment costs of the generators and storages, and the marginal costs, respectively.

We observe from Figure A.1 that although not installed in the base scenario, the carrier-technology pair electricity-pth is installed in Brandenburg if the unit capacity costs are changed. Yet, we also observe that the capacity of electricity-pth in Berlin is insensitive to the unit capacity investment costs of the alternative technologies.

Despite substantial cost perturbations among alternative technologies, the absence of electricity-pth installation at Berlin, mirroring the base scenario, underscores its economic infeasibility within this specific scenario instance. Conversely, deviations of up to 50% in installed capacity for H2-gt and electricity li-ion battery in Brandenburg compared to the base scenario highlight their heightened sensitivity to capacity installation costs, rendering them the most sensitive technologies in this regard. Figure 5 shows that contrary to the case in Berlin, in Brandenburg, investment in electricity-heatpump-large and CH4-boiler-large carrier-technology pairs are highly sensitive to the changes in the unit storage capacity costs, increasing up to 8.7 MW to 150 MW and 12.7 MW to 300 MW, respectively. Figure A.2 reveals that some variables are not affected by uncertainties in marginal costs at all; in terms of installed capacities.

The sensitivity analysis of capacity in Figure A.1 shows that, in Brandenburg, solar-pv reacts more sensitively to a change in investment costs than wind energy. This is due to investment in fluctuating RES is strongly influenced by their generation profiles and their relationship to demand profiles. From the model output data on balance we see only around 30% of wind and solar-pv electricity is needed to cover the electricity demand, while a large proportion is used to cover heat demand. For the increased heat demand in winter, wind is a more cost-effective solution than solar-pv, as the wind generation profile has a higher overlap with the heat demand profile in these months. This means that a larger proportion of the

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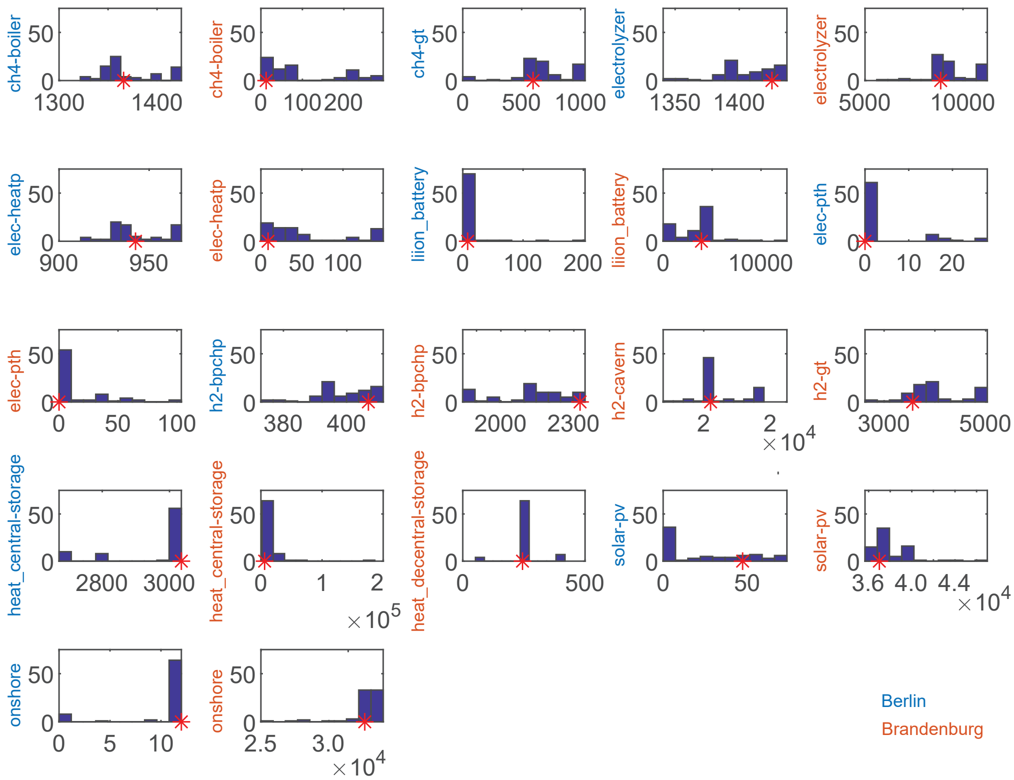

Figure 5: Capacity Sensitivity to Unit Capacity Investment Cost of Storages (in MW Installed Capacity/ MWh for storage technologies), with heatp. and boiler referring to the large variant of those

4.4. Impact of Input Costs on Particular Technologies

The dashboard and the sensitivity analysis results also enable us to investigate the impact of altering the cost of particular technologies. Analysis of the effect of increasing respectively decreasing the marginal costs for wind onshore on the installed capacities reveal a dependency of capacities of electricity generation from CH4 and power-to-gas to the wind onshore marginal cost, especially by an increase in the installed capacities when the cost decreases (without figure).

Last but not least, we investigate the sensitivity of the marginal costs of the available technologies and carriers to the changes in unit capacity investment costs of wind onshore and solar-pv. Figure A.3 shows the increase in the capacity cost has contrasting effects on the marginal costs of technologies such as decreasing gas turbine vs. increasing li-ion battery. Yet, this contrasting effect is not observed when we increase the unit capacity cost for solar-pv. However, decreasing the capacity cost of solar-pv has a similar impact on the li-ion battery marginal costs as decreasing the capacity costs of wind onshore.

5. CONCLUSIONS

We present a method that integrates LP sensitivity analysis, optimization, and data visualization techniques to facilitate decision-making under uncertainty, particularly in contexts involving competing technologies and varied decision-maker preferences. Demonstrating the efficacy of our approach through a real-world case study in Berlin and Brandenburg, we showcase its capabilities in accommodating diverse decision-making perspectives, from urban to suburban areas. Employing visualizations enables the participation of

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decision-makers without mathematical background to discuss design alternatives. The graphical treatment of hundreds of scenarios makes it possible for decision-makers to explore technological alternatives with respect to their goals and regional specifics. Geographical and settlement structures, national targets, technology costs and demand projections weigh account into the design of energy system. They are enabled to better weigh choices with regard to successful sustainable energy system transformation paths, though at the expense of cost optimality but in favor of other transformational success factors such as timely feasibility of technical transformation or social acceptance of technologies. Thus, decision-makers are enabled to conceive policies to trigger more robust development paths towards a net zero energy system. The proposed method also provides a foundational tool for assessing the design alternatives to scrutinize for structural uncertainties in the continuation of the study.

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A. APPENDIX

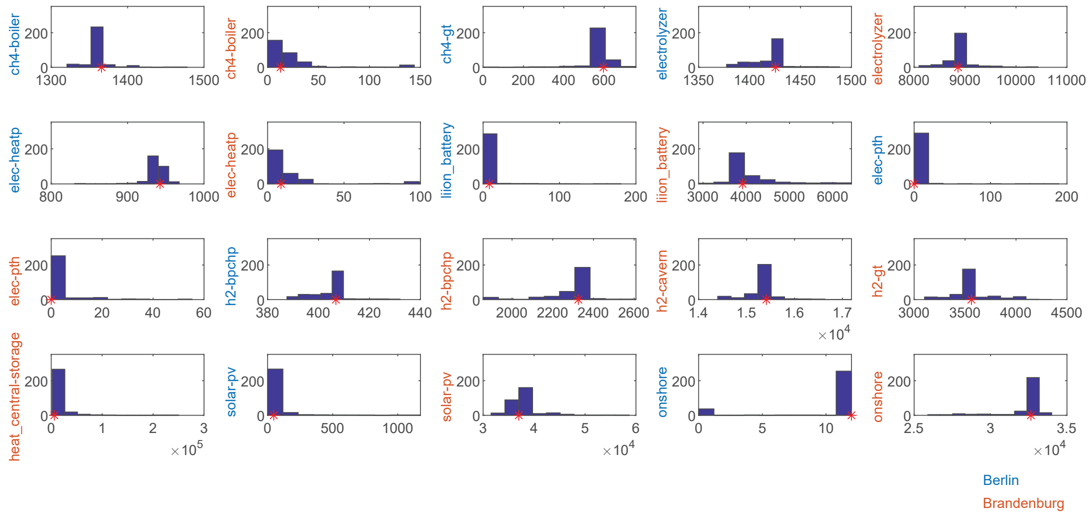

Figure A.1: Capacity Sensitivity to Unit Capacity Investment Costs (in MW Installed Capacity/ MWh for storage technologies), with heatp. and boiler referring to the large variant of those

https://doi.org/10.52202/077185-0115

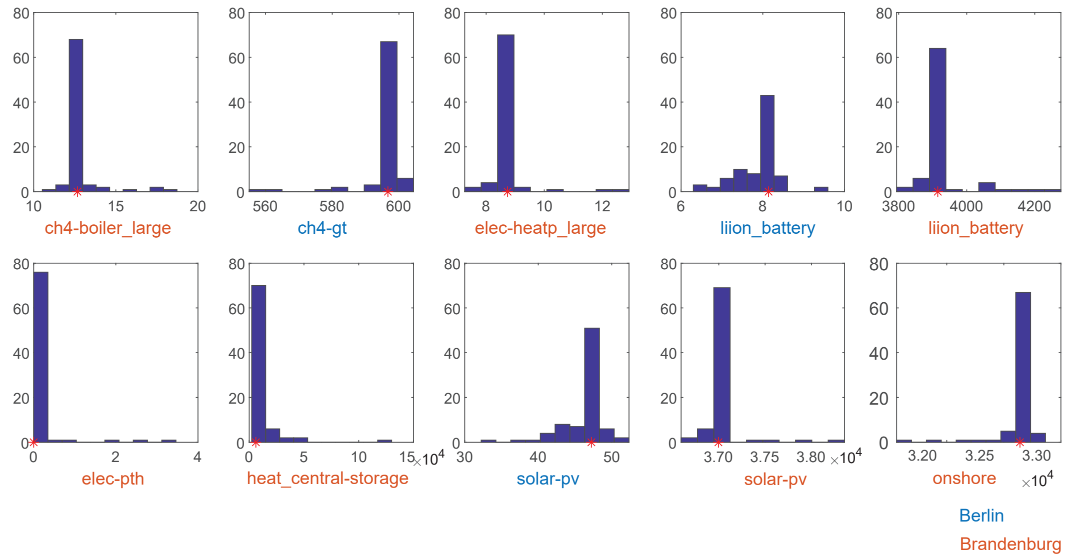

Figure A.2: Capacity Sensitivity to Marginal Costs (in MW Installed Capacity/ MWh for storage technologies)

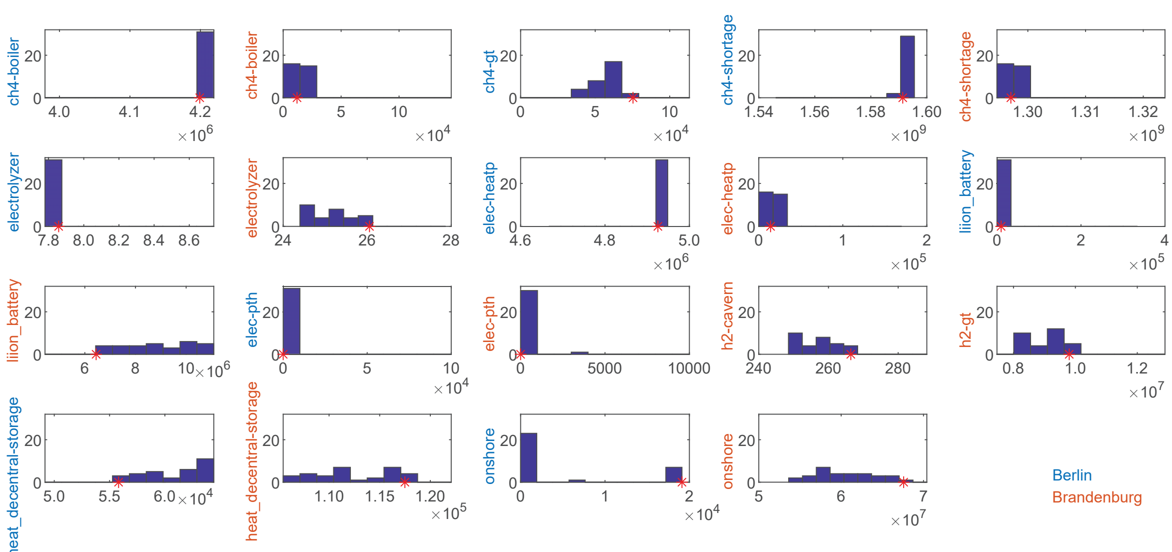

Figure A.3: Sensitivity of Marginal Cost to Increase in Unit Capacity Costs of Wind Onshore (in EUR), with heatp. and boiler referring to the large variant of those

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