Sensitivity of the energy system to perturbation of the capacity factor of the PV and wind

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Overview

Decarbonizing the energy system by increasing the use of variable renewable energy (VRE) sources is essential for mitigating climate change. Using energy system models is crucial in planning future energy mixes and evaluating potential policies. As VRE sources gain prominence, these models become increasingly dependent on weather conditions, necessitating careful consideration of uncertainties in factors such as capacity factor (CF).

Due to the limited temporal and spatial availability of observed CF data, these observations are not used in long-term planning or studies requiring new assumptions about factors like the type and distribution of installed technologies. Instead, CFs are derived from climate data. However, CFs calculated from climate data are prone to uncertainties, which can arise either from biases in the climate data itself (Staffell & Pfenninger, 2016)(Pfenninger & Staffell, 2016) or from the methodologies used to convert climate data into CFs (Moraes et al., 2018).

The impact of uncertainties in CF datasets on energy systems has been highlighted in recent studies. For example, Kies et al. (Kies et al., 2021) demonstrated that CF datasets derived from different climate data sources and conversion processes can lead to significant variations in energy system model results. However, this study did not explicitly link changes in model outputs to variations in CFs. Similarly, Mathews et al. (Mathews et al., 2023) focused on the effects of different climate datasets on the operation of battery storage systems but did not extend their analysis to the broader impacts on total system costs or optimal technology investments. This underscores the need for a more comprehensive analysis that directly connects variations in CF datasets to their broader implications on energy system modeling outcomes.

Methods

To understand the impact of different types of uncertainty in capacity factors (CFs) on energy system outputs, various perturbed CF datasets of photovoltaic (PV) and wind are given as input to the energy system model, and the resulting absolute changes in total system costs, installed capacities, and their elasticity are assessed. Two types of perturbations are applied: uniform perturbations, where CFs are perturbed by the same amount across all time steps, and quantile range perturbations, where only one of the selected quantile ranges are perturbed, quantile ranges are equally spaced intervals on the sorted CF dataset. In both cases, the average change in CF is kept constant for a given perturbation value. Moreover, different magnitudes and signs of perturbations are included.

The EOLES energy system model (Shirizadeh & Quirion, 2023), an investment and dispatch optimization model, is adapted for this study. The version of the EOLES energy system model used in this study allows for the possibility of unserved demand, with generation technologies including PV, wind, run-of-river hydro, lake, nuclear, and combined-cycle gas turbines (CCGT), and storage technologies comprising batteries and pumped hydro storage (PHS). The effects of CF perturbations are analyzed in two scenarios: one where only dispatch is optimized and another where both capacity and dispatch are optimized. Additionally, the study compares the system's sensitivity to CF perturbations with its sensitivity to changes in capital expenditures (CAPEX), providing insights into the relative importance of CF uncertainty versus CAPEX, which has traditionally received more attention in the literature.

Results

The results show that system outputs are more sensitive to wind CF perturbations than PV CF perturbations. For example, the elasticity of the total system cost to wind CF perturbations is, on average, seven times greater than that for PV CFs. This difference arises from the closer alignment of wind CFs with peak demand and the higher optimal installed capacity of wind. Both PV and wind CF perturbations have a greater impact in the lower quantile ranges, which correspond to low-generation events, compared to the higher quantile ranges, which correspond to high-generation events.

The heightened sensitivity to CF perturbations in the initial quantile ranges is due to the presence of a larger number of time steps with lost load. As a result, CF perturbations lead to changes in lost load or generation from dispatchable units. In contrast, in the final quantile ranges, the percentage of time steps with negative residual demand is higher. Since generation exceeds demand during these times, CF perturbations—if they maintain negative residual demand—do not affect the generation from different technologies or the total system cost.

In scenarios with fixed installed capacities, negative CF perturbations result in considerably higher sensitivities than positive perturbations, on average, around 38 times higher. Furthermore, the sensitivities to CF perturbations, when both installed capacities and dispatch are optimized, are found to be comparable in magnitude to those caused by changes in capital expenditures (CAPEX).

Installed capacities generally show higher elasticities than those observed in total system costs, which is a common behavior in energy system studies. Moreover, the majority of the positive perturbations of wind or PV CF lead to increases in their installed capacities, while negative perturbations result in the opposite effect. Furthermore, the majority of perturbations reveal a substitutability effect between the installed capacities of PV or wind (the technology with perturbed CF) and nuclear capacity, as well as a complementarity effect with the installed capacity of CCGT.

Conclusions

In conclusion, our study demonstrates that the average CF is a poor predictor of energy system outputs. Despite consistent average changes in CFs across different perturbations, they lead to varying installed capacities and total system costs. The energy system model's heightened sensitivity to CF perturbations at lower quantile ranges and under negative perturbations when installed capacities are fixed underscores the importance of ensuring the accuracy of the CFs in the initial quantile ranges and mitigating potential negative errors. Furthermore, uncertainties in CF datasets used for prospective studies and capacity planning deserve increased attention, as the sensitivity of the energy system to them is comparable to that of factors like CAPEX, which receives more emphasis. We suggest that future research focus on identifying possible errors in each step of calculating CFs. This includes examining the choice of climate data, the selection of power curves, PV cell models, the choice of bias correction methods, and the choice of intraregional VRE capacity distribution.

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