Supplementary Information

1. **Developing new cost-supply curves for onshore wind, using wind energy deployment across U.S. states.**

One key balancing feedback for the diffusion of renewables in FTT:Power is the cost-supply curve (CSC), which posits that investors first choose the windiest locations for wind turbines and that the capacity factor for new wind turbines would therefore decrease as more wind is deployed. A similar assumption is used for solar, but with smaller capacity factor penalties. Using empirical data of U.S. wind deployment, we find little support for this assumption and develop a new cost-supply curve consistent with this data.

We use the US Wind Turbine Database (USWTDB)[1] to extract project-level information, including turbine geolocation, project name, year of installation, and installed capacity. This dataset enables accurate estimation of yearly and cumulative wind energy deployment. TP estimates[2] capture the maximum feasible wind energy generation based on land availability, resource quality, and exclusion criteria. To assign representative capacity factors (CFs) to installed wind projects, we use modelled mean capacity factors[3] associated with specific geolocations. A k-d tree nearest-neighbour search is employed to match each installed turbine's coordinates with the closest modelled CF value, subject to a distance threshold of 10 km. The resulting CFs are then averaged across projects annually and by state to capture temporal trends.

To understand the long-term evolution of location choice in high-deployment regions, we analysed historical trends in resource capacity factor (CF) for U.S. states where more than 10% of their estimated technical potential (TP) has been utilized. By focusing on the states with significant wind deployment, we aim to explore whether modelled CF has changed over time if newer projects are sited in progressively lower-quality resource areas. Note, we do not look at realised CFs, as wind turbines have become better over time. The results are summarized in a bar chart showing the slope of the CF trend for each qualifying state (Fig. 1). Negative slopes indicate a decline in CF over time, while positive slopes suggest improvement. States such as New Hampshire (NH), West Virginia (WV), and California (CA) exhibited downward trends. On the other hand, states like Pennsylvania (PA) and Maryland (MD) showed increasing trends. For the 8 U.S. states where wind energy installations have exceeded 10% of their estimated technical potential, the median change in average capacity factor is −0.46% per 10% of technical potential utilization, with a range of -1.66% to +0.37%, indicating a tendency toward a slight capacity factor decline with increasing resource deployment in these regions. While computing the statistics for old cost-supply curve from FTT:Power, we found the CF change per 10% TP utilization to be 11.6%.

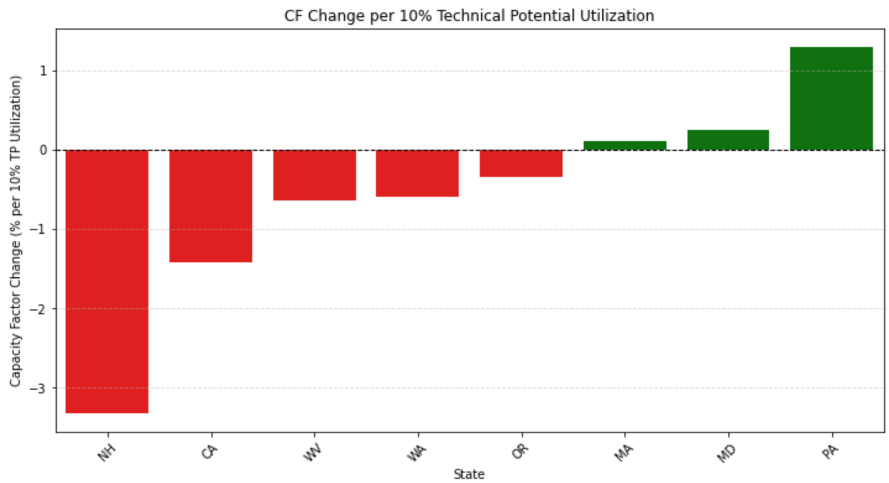

Figure 1: Statewise trends in average capacity factor over time for U.S. states with >10% technical potential (TP) utilization. Red bars indicate decreasing trends and dark green bars an increasing trend.

To capture the empirical relationship between CF and TP utilization, we test the functional form: $\boldsymbol{CF = 1 - e^{-k(1-x)}}$, where $\boldsymbol{x}$ is the normalized TP utilization, and $\boldsymbol{k}$ is a curvature parameter. This exponential model is selected to reflect the near-zero trend of resource quality with increasing deployment, while ensuring that expansion slows down as deployment approaches the technical potential. For each state and each year, we compute the cumulative installed capacity (MW) by summing annual installed capacities. This cumulative capacity is then normalized by the corresponding state's TP value to compute the utilization percentage, i.e., the share of TP that has been deployed over time. This metric, referred to as TP utilization, ranges from 0 to 100% and serves as the independent variable in our modelling of CF degradation. We explore a couple of fitting strategies: CFs are normalized by the mean CF of each state to reduce heterogeneity across states. This method is applied to the full dataset (Fig. 2). In other such analysis, we restrict analysis to states where TP utilization exceeds 10%.

We filtered the dataset to include only states where maximum TP utilization exceeded 10%. Within this, we again applied the exponential fitting on the full utilization range (Fig. 2).

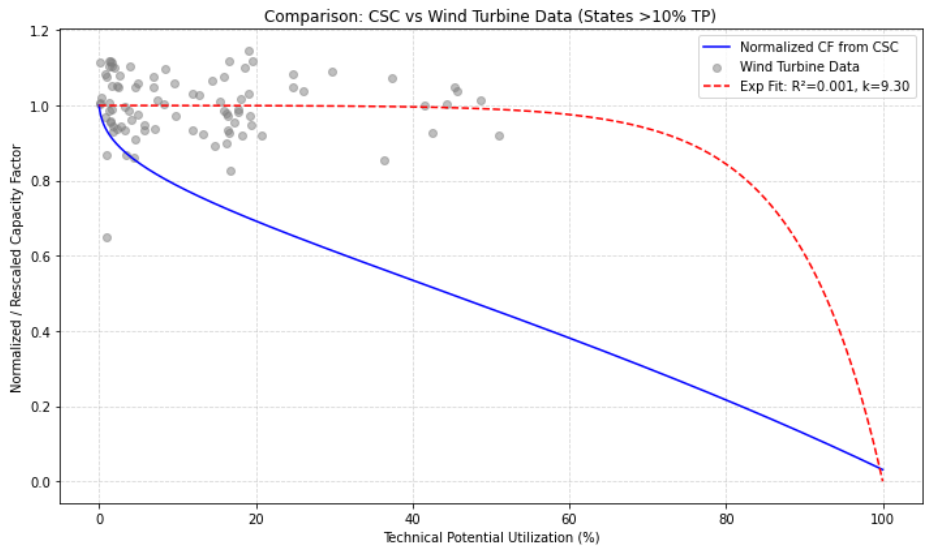

Figure 2: Exponential fit of rescaled capacity factor against technical potential (TP) utilization across 8 U.S. states. The blue curve represents normalized capacity factor derived from the original CSC formulation. The grey dots indicate wind turbine deployment data by state, rescaled by each state's average capacity factor. Only states with at least 10% technical potential utilization are shown.

Our results indicate that wind speed is not the main determining factor for siting in the early and mid-transition. The proposed exponential fit reflects this behaviour, while preserving the functionality of stopping expansion of wind energy when approaching the technical potential.

References

1) Hoen, B.D., Diffendorfer, J.E., Rand, J.T., Kramer, L.A., Garrity, C.P., and Hunt, H.E., 2018, United States Wind Turbine Database V8.0 (February 25, 2025): U.S. Geological Survey, American Clean Power Association, and Lawrence Berkeley National Laboratory data release. https://doi.org/10.5066/F7TX3DN0.
2) Lopez, Anthony, Billy Roberts, Donna Heimiller, Nate Blair, and Gian Porro. US renewable energy technical potentials. a GIS-based analysis. No. NREL/TP-6A20-51946. National Renewable Energy Laboratory (NREL), Golden, CO (United States), 2012.
3) Lopez, Anthony, Pavlo Pinchuk, Michael Gleason, Wesley Cole, Trieu Mai, Travis Williams, Owen Roberts, Marie Rivers, Mike Bannister, Sophie-Min Thomson, Gabe Zuckerman, and Brian Sergi. 2024. Solar Photovoltaics and Land-Based Wind Technical Potential and Supply Curves for the Contiguous United States: 2023 Edition. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-87843.

2. Gamma value automation

In each of the FTT models, gamma values are used to capture non-monetary elements to decision making. In previous work, the gamma values were determined manually. See [1]. Gamma values were defined as an added value to the levelised cost, or in the case of the transport model, added to the logarithm of the levelised costs. Here, we instead define γ as a scaling factor between the true costs and the costs seen by the decision-maker:

$$C_{seen} = C_{true} * (1 + \gamma) \tag{1}$$

We assume that the γ values remain between -1 and +1. We use simulated annealing with regulation to find appropriate gamma values. The methodology seeks to minimise the difference in the relative rate of change between the last 5 years of the historical period and the first 5 years of the simulated period. That is, we calculate

$$g = \frac{dS_i}{dt} / S_i \tag{2}$$

We then compute the difference between historical growth (g_h) and simulated growth rates (g_s).

To prevent large gamma values, which may overwhelm the endogenous dynamics, we apply a regulation parameter λ, so that we minimise the following score

$$score = \tanh(-|g_s - g_h| - \lambda\gamma^2) \tag{3}$$

The simulation starts with all gamma values being zero. For each technology and each country, a small gamma value is added in each iteration, randomly distributed ($\mathcal{N}(0, \gamma_{\text{sd}}^2)$). In addition, at each time step, 5% of the country-average gamma value is subtracted from each technology, to ensure values are distributed more evenly around zero, making cross-country comparisons easier and ensuring that the simulation does not get stuck at the minimum and maximum gamma values.

The model is run. For each country-technology combination where the new gamma value is an improvement, the gamma value is accepted. For each new gamma value that does not improve the score, the gamma value is accepted with a chance:

$$e^{(score - score_{lag})/T} \tag{4}$$

The temperature T slowly decreased over time with a cooling rate T_c and a starting temperature T_0, so that $T = T_0 * T_c^{it}$, where it is the iteration. The initial temperature is set as the average non-zero change in score after the first iteration divided by 5. A single run stops when convergence is obtained or when there have been more than 150 iterations. The convergence criterion is (again, only taking non-zero values for γ and lagged γ):

$$\frac{1}{N} \sum_{i=1}^{N} |\gamma_i - \gamma_{\text{lag},i}| < \epsilon \tag{5}$$

The simulation is performed N_{runs} times, to prevent a local minimum. For each country and model, the best set of γ values is chosen, to minimize the sum of scores for that country and model.

The table below shows the values used in the simulation.

T_c	0.96	λ	0.2
$T_{0,init}$	0.004	ϵ	0.015
N_{runs}	5	γ_{sd}	0.2

Table 1: Parameter table

References

[1] Mercure, J.-F., Lam, A., Billington, S. & Pollitt, H. Integrated assessment modelling as a positive science: Private passenger road transport policies to meet a climate target well below 2°C. *Climatic Change* **151**, 109–129 (2018).