

MAPPING THE WHOLESALE MARKET VALUE OF SOLAR POWER ACROSS THE UNITED STATES

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Overview

Technological improvement and economies of scale have led to sustained reductions in the levelized cost of electricity (LCOE) for solar photovoltaics (PV), and the LCOE for utility-scale PV is now at or below the average retail price of electricity across most of the United States. [1] At the same time, numerous studies have projected a declining market value for solar PV as PV penetration increases, resulting from wholesale electricity price suppression during hours of the day with significant zero-marginal-cost solar generation. [2–4] In general, prior studies have explored the market value of solar at the resolution of a balancing area, state, or country, and have not captured spatial variations in value or the influence of different PV system design parameters on the market value of PV electricity.

Here, we combine temporally- and geographically-resolved nodal locational marginal prices (LMPs) with a time-resolved PV performance model to calculate the wholesale market value of solar PV electricity at over 13,000 U.S. pricing nodes from 2010 through 2017. We highlight variation in the value of solar within and between different U.S. Independent System Operators (ISOs) and trends in the value of solar over time, and we explore various strategies for increasing the value of PV electricity at a given location through appropriate choice of PV module technology, PV array orientation, and solar tracking strategy. Using the simulated PV revenues, we calculate break-even levels for overnight system cost that would make PV electricity competitive at each of the nodes analyzed.

Methods

The modeled yearly revenue of a PV array for a given pricing node is calculated from the product of the LMP at that node (at hourly resolution for day-ahead prices and at either 5-minute or hourly resolution for real-time prices) and the modeled power output of a solar generator at that node, summed over the year of interest. LMPs and node locations are taken from the respective ISOs (CAISO, ERCOT, MISO, PJM, NYISO, and ISONE). Historical satellite-derived solar irradiance data are taken from the National Solar Radiation Database (NSRDB), and are matched to the geographic location of each node for the year of interest. [5] Solar PV electricity generation is calculated using the PVLIB Toolbox available from Sandia National Laboratory, factoring in the effect of array orientation, system and inverter losses, temperature-induced losses, and inverter overloading, with the optional incorporation of 1-axis solar tracking. [6] PV performance model results are validated by comparing modeled energy generation with monthly reported energy generation for hundreds of utility-scale PV plants from U.S. Energy Information Administration reports. [7]

Results

Our results demonstrate high spatial variability in the wholesale value of PV electricity within ISOs: the highest-value nodes within the CAISO, ERCOT, PJM, and NYISO networks demonstrate more than double the yearly revenue of the lowest-value nodes within the same system in any given year. In general, the sunniest locations are not necessarily the best locations to install solar: the 2015 median yearly revenues across all nodes in the relatively low-insolation New York and New England ISOs (NYISO and ISONE) are higher than in the California and Texas ISOs (CAISO and ERCOT). Significant variations in the wholesale value of solar are also observed from year to year, primarily driven by variations in the price of natural gas: the median nodal wholesale revenue of a solar generator in ISONE would have been roughly twice as high in 2014 as in 2016. In general, changes in the price of electricity over time and between different locations have a larger effect on the predicted revenue of a solar generator than variation in the solar resource between locations. Combining these results with a simple financial model enables a calculation of the maximum upfront cost for solar PV to break even on the wholesale market at each node.

Our methodology also enables the optimization of PV plant design for wholesale revenue, rather than simply for capacity factor. In California, where increased PV penetration has resulted in a pronounced dip in wholesale electricity prices in the middle of the day, the optimal orientation for a capacity-factor-maximizing fixed-tilt array is roughly due south, while the optimal orientation for a revenue-maximizing fixed-tilt PV array is found to shift increasingly westward over time. Curtailment of PV generation during negative-price intervals further increases PV revenues on the real-time market in 2017.

Conclusions

The significant variation in the locational value of solar electricity noted in this work has implications for both developers and policymakers. For a solar developer, the observed variation in the predicted revenue from a solar generator across different nodes in a given ISO can be used to guide choices on plant siting. As electricity price profiles change with the deployment of additional PV capacity, the optimization of plant design parameters for electricity revenue generation rather than for capacity factor alone will become even more important. For a policymaker, the fact that the market value of solar can vary by more than a factor of two between regions of similar insolation in a given balancing area highlights that volumetric reimbursement schemes for solar producers who are not directly exposed to wholesale prices do not necessarily lead to optimal siting decisions. A “locational value of solar” tariff for distributed solar could help enable the preferential installation of solar at locations that add value to the grid. Similar methods can be used to map the wholesale market value of wind energy and energy storage, and the incorporation of capacity and reserve prices could present a more complete picture of the market value of these distributed energy resources.

The results presented here are for a marginal generator acting as a price-taker. Tracking the evolution in solar value and penetration over time and factoring in variations in other drivers of electricity price, such as the magnitude of net demand and the price of natural gas, will enable an empirical determination of the relationship between solar penetration and the market value of solar, which could then be used to determine cost targets for solar to remain competitive at increased levels of deployment.

References

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