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THE COAL COST CROSSOVER: ECONOMIC VIABILITY OF EXISTING COAL COMPARED TO NEW LOCAL WIND AND SOLAR RESOURCES

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America has officially entered the "coal cost crossover" – where existing coal is increasingly more expensive than cleaner alternatives. Today, local wind and solar could replace approximately 74 percent of the U.S. coal fleet at an immediate savings to customers. By 2025, this number grows to 86 percent of the coal fleet.

This analysis complements existing research[2] into the costs of clean energy undercutting coal costs, by focusing on which coal plants could be replaced locally (within 35 miles of the existing coal plant) at a saving.

It suggests local decision-makers should consider plans for a smooth shut-down of these old plants—assessing their options for reliable replacement of that electricity[3], as well as financial options for

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[1] The authors would like to thank Joe Daniel, Harriet Moyer Aptekar, Jeremy Fisher, Uday Varadarajan, Ric O'Connell, Taylor McNair, and Sonia Aggarwal for their helpful feedback on this report. Any remaining errors are the responsibility of the authors.

[2] Carbon Tracker Institute, *No Country for Coal Gen – Below 2° C and Regulatory Risk for US Coal Power Owners*, September 2017, https://www.carbontracker.org/reports/no-country-for-coal-gen-below-2c-and-regulatory-risk-for-us-coal-power-owners/; Pacificorp, *2019 Integrated Resource Plan (IRP) Public Input Meeting*, December 2018, https://www.eenews.net/assets/2018/12/05/document_cw_01.pdf.

[3] Joshua Novacheck, Greg Brinkman, and Gian Porro, *Operational Analysis of the Eastern Interconnection at Very High Renewable Penetrations*, National Renewable Energy Laboratory, September 2018, https://www.nrel.gov/docs/fy18osti/71465.pdf; Mark Dyson and Alex Engel, A Low-Cost Energy Future for Western Cooperatives, Rocky Mountain Institute, 2018, https://www.rmi.org/wp-content/uploads/2018/08/RMI_Low_Cost_Energy_Future_for_Western_Cooperatives_2018.pdf.

communities dependent on those plants[4].

Ultimately, this report begins a longer conversation about the most cost-effective replacement for coal, which may include combinations of local or remote wind, solar, transmission, storage, and demand response.

INTRODUCTION & RESULTS

Coal generation is at a crossroads in the United States, or more precisely at a "cost crossover." Due to the rapid recent cost decline of wind and solar,[5] the combined fuel, maintenance, and other going-forward costs of coal-fired power from many existing coal plants is now more expensive than the all-in costs of new wind or solar projects. This cost crossover raises substantial questions for regulators and utilities as to why these coal plants should keep running instead of new renewable power plants.

To determine which coal plants are facing this cost crossover with renewables, Energy Innovation partnered with Vibrant Clean Energy (VCE) to compile a dataset of coal, wind, and solar costs.[6] For simplicity, the modeling compares each coal plant's marginal cost of energy (MCOE) to the lowest levelized cost of energy (LCOE) for wind or solar resource localized around that coal plant. Restricting replacement to local resources makes this analysis conservative, considering most coal, wind, and solar all travel from more remote locations to load centers via transmission.

Our research finds that in 2018, 211 gigawatts (GW) of existing (end of 2017) U.S. coal capacity, or 74 percent of the national fleet, was at risk from local wind or solar that could provide the same amount of electricity more cheaply. By 2025, at-risk coal increases to 246 GW – nearly the entire U.S. fleet.[7]

Definitions in this analysis:

"Local" means within 35 miles.

"At risk" coal means local wind or solar could replace the coal plant's total output (on a kilowatt-hour basis) at an all-in cost lower than the existing coal plant's ongoing marginal costs.

"Substantially at risk" coal means local wind or solar could replace the coal plant's total output at an all-in cost >25% lower than the existing coal plant's ongoing marginal costs.

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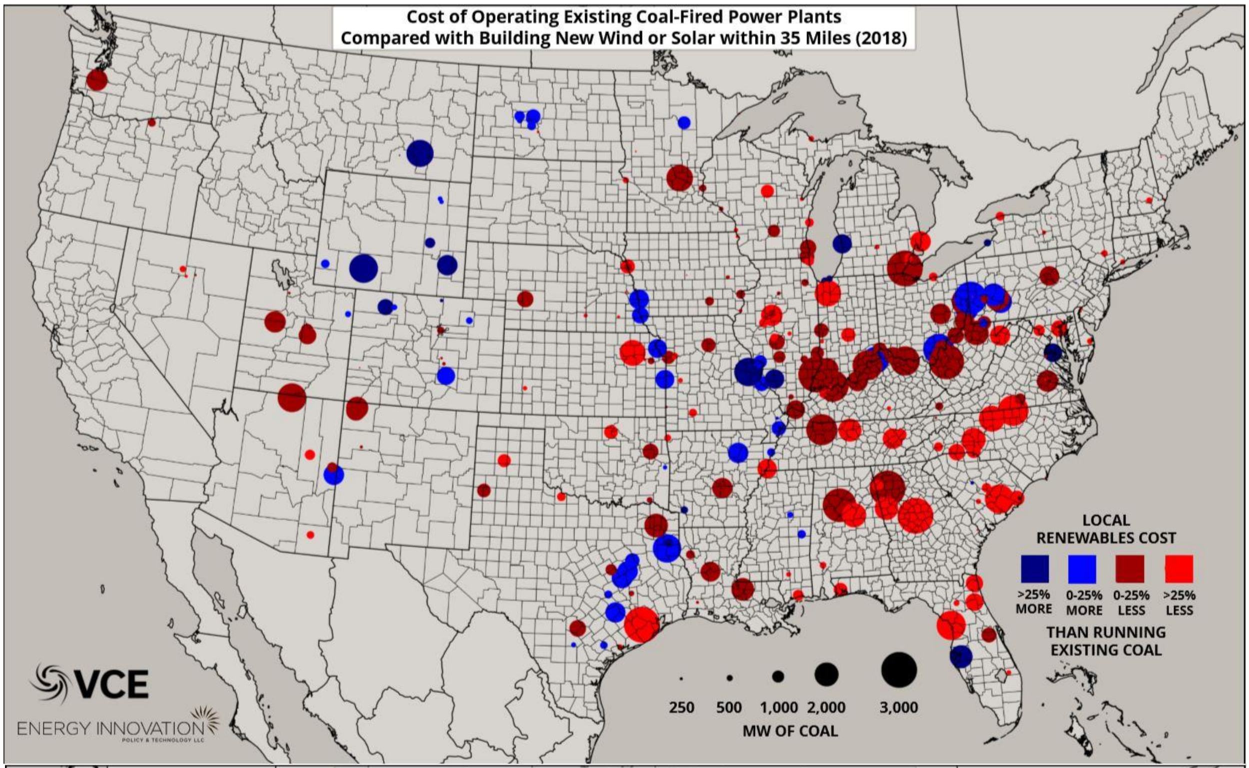
[4] Sonia Aggarwal, "Billions At Stake: Should We Invest In Struggling Power Plants Or Communities Facing Closures?" *Forbes*, August 23, 2018, https://www.forbes.com/sites/energyinnovation/2018/08/23/billions-at-stake-should-we-invest-in-struggling-power-plants-or-communities-facing-closures/#b62238a1f687.

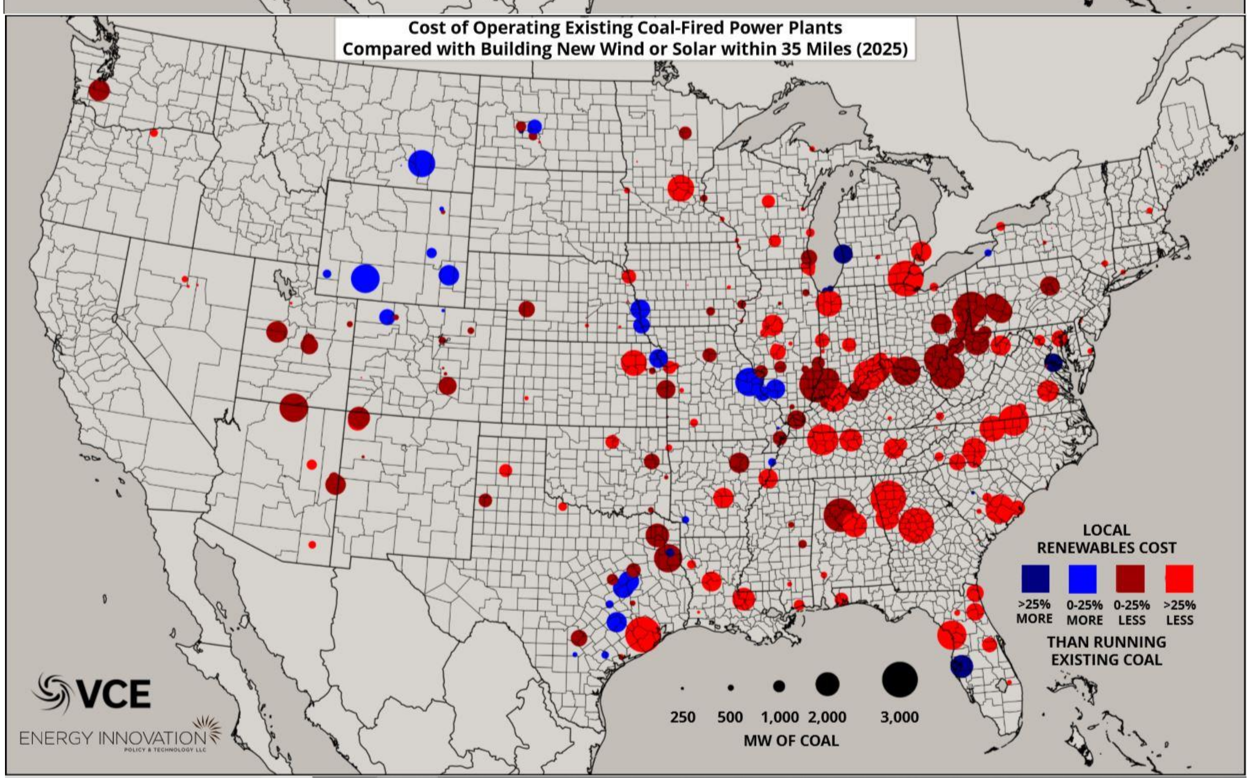
[5] Megan Mahajan, "Plunging Prices Mean Building New Renewable Energy Is Cheaper Than Running Existing Coal," *Forbes*, December 3, 2018, https://www.forbes.com/sites/energyinnovation/2018/12/03/plunging-prices-mean-building-new-renewable-energy-is-cheaper-than-running-existing-coal/.

[6] VCE's WIS:dom model uses granular wind speed and solar irradiance data for nine-square-kilometer (3-km x 3-km) cells across the entire U.S. to paint an accurate picture of LCOE, making this a uniquely granular analysis.

[7] The VCE compiled dataset computes approximately 286 GW of coal-fired power plants as of January 1st, 2018. Since that date, rapid retirements and re-firing with natural gas has occurred, in part, due to the cost pressure that we identify in this study.

Furthermore in 2018, 94 GW of existing U.S. coal capacity was deemed substantially at risk from new local wind and solar that could undercut ongoing costs of existing coal by at least 25 percent. By 2025, substantially at risk coal increases to 140 GW – almost half the U.S. fleet – even as federal renewable energy tax credits phase out. Given uncertainties in publicly available coal cost data, the tier of coal plants "*substantially at risk*" could, with high confidence, be





replaced with renewable energy at an immediate cost savings. State-by-state data as well as a national-level dataset detailing these findings are available as a companion to this report.

The VCE dataset reveals the going-forward costs for the vast majority of coal plants fall between \$33 – 111 / megawatt-hours (MWh). Costs in 2018 for solar are more tightly clustered, between \$28 – 52 / MWh, while wind costs vary more widely based on locational resource quality, falling between \$13 – 88 / MWh, with a high number of very costly outliers in windless regions.

The crossover between new renewable and coal running costs is just one important part of shutting down existing coal plants – replacing coal plants with new wind and solar energy is much more complex in practice. The purpose of this report is to act as a conversation primer for stakeholders and policymakers where the math points to cheaper options that could replace coal plants at a savings to customers. Any decision on how to proceed will require further modeling of grid impacts and alternative sources of reliability services, as well as the possibility for even cheaper renewable replacements further away than the 35-mile maximum radius considered in this report.[8]

Regardless, any coal plant failing the cost crossover test should be a wake-up call for policymakers and local stakeholders that an opportunity for productive change exists in the immediate vicinity of that plant.

Building local renewables in the immediate vicinity of coal plants implies wind and solar could replace local jobs, expand the tax base, reuse existing transmission, and locate in the same utility service territory. But these constraints are quite restrictive. Utility planners, regulators, and customers could save additional money by looking further afield. For example, Colorado plans to replace its coal fleet with strategically located wind and solar resources around the state.[9] The VCE WIS:dom model and others can accurately analyze the viability of transitioning from dispatchable power sources like coal to variable resources like wind and solar.

The unpaid capital balance owed to investors in coal plants falls outside a coal plant's MCOE. Though this balance should not factor into the economic viability of the plant (after all, it's easier to repay debt if utilities are meeting current obligations more cheaply), potential stranded asset value of at-risk coal plants reaches into the tens of billions. A recent series of America's Power Plan policy briefs[10] highlight different financial tools policymakers can consider to retire uneconomic coal-fired generation while balancing consumer, community, and investor concerns.

[8] VCE's algorithm selected wind or solar resources immediately adjacent to the coal plant, and moved outward until renewable energy replaced the output of the coal plant. 35 miles is the furthest away from the coal plant the model had to go to fill this need. The algorithm is described in Appendix C.

[9] "Colorado Energy Plan," Xcel Energy, https://www.xcelenergy.com/company/rates_and_regulations/resource_plans/colorado_energy_plan.

[10] "Managing The Utility Financial Transition From Coal to Clean," Energy Innovation: Policy and Technology LLC, https://energyinnovation.org/publication/managing-the-utility-financial-transition-from-coal-to-clean-2/.

CORE DATASETS

This report uses two data sources to construct its unique plant-by-plant analysis: LCOE and MCOE. Current and future LCOE data for wind and solar projects are on a fine resolution scale, allowing policymakers to directly see wind and solar opportunities in their geography. VCE has created several high-resolution wind and solar LCOE maps across the U.S. using detailed weather models for power production at a nine-km^2 geographic resolution, multiple wind hub-heights, and a five-minute temporal resolution. Modeling details are provided in Appendices A & B.

The wind and solar LCOE maps in this report include 2018 LCOE estimates by VCE for each technology, including current tax benefits and regional cost modifiers. They clearly show attractive pricing for both technologies across the U.S. as low as $15 per MWh for wind and $28/MWh for solar in 2018. Note that wind LCOEs have more geographic variation and hence the color scales differ from the solar color scales.

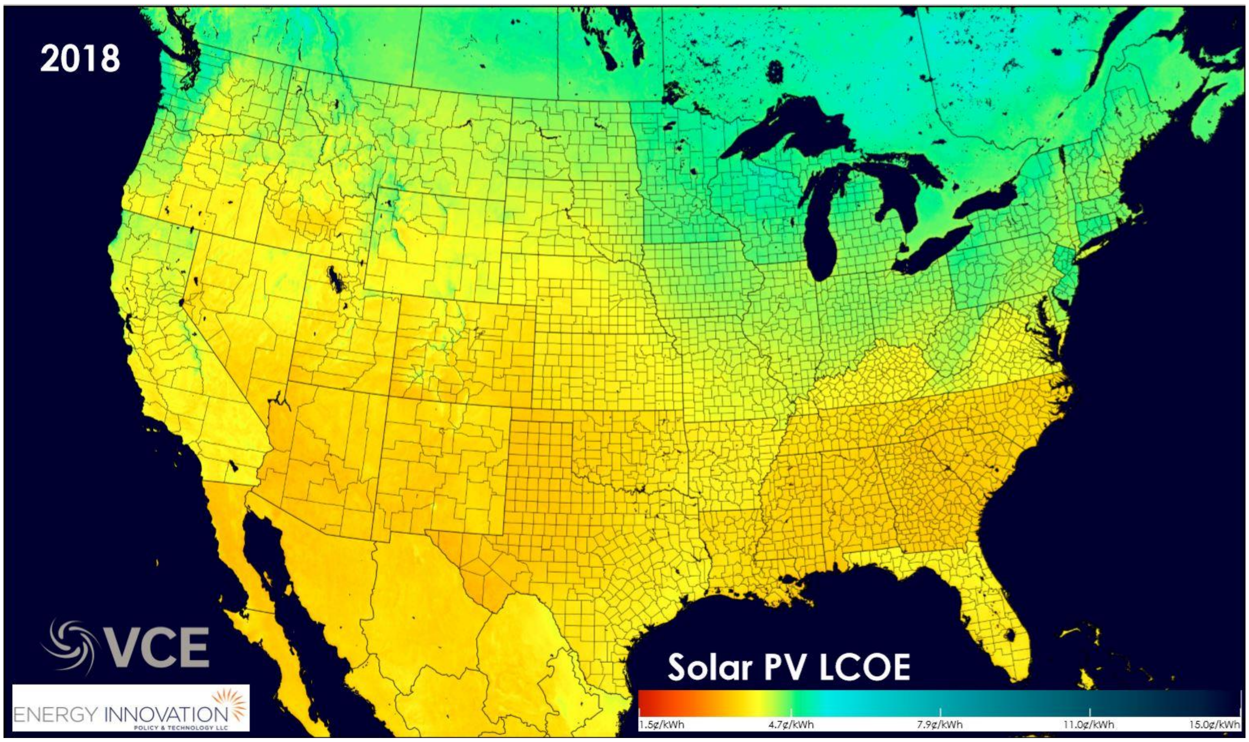
We also include the VCE 2025 estimates of wind and solar LCOE using the low-case NREL Annual Technology Baseline (ATB)11 cost projections. In 2025, despite the loss of federal tax incentives,12 future cost declines mean that future pricing continues to be attractive. High-resolution images of the wind and solar LCOE maps are available for download, allowing users to zoom in at a fine-scale.

VCE also provided plant-by-plant estimates of the current MCOE for U.S. coal plants. This dataset was created for existing U.S. coal-fired power plants by combining publicly available information. Data was collected from FERC Form 1, EIA Form 860, and EIA Form 923 for the calendar year 2017. The extracted information includes amount of fuel burned, average power plant heat rate, emission factors, capital investments, pollution controls, fixed operations and maintenance (O&M) costs, and variable O&M costs.

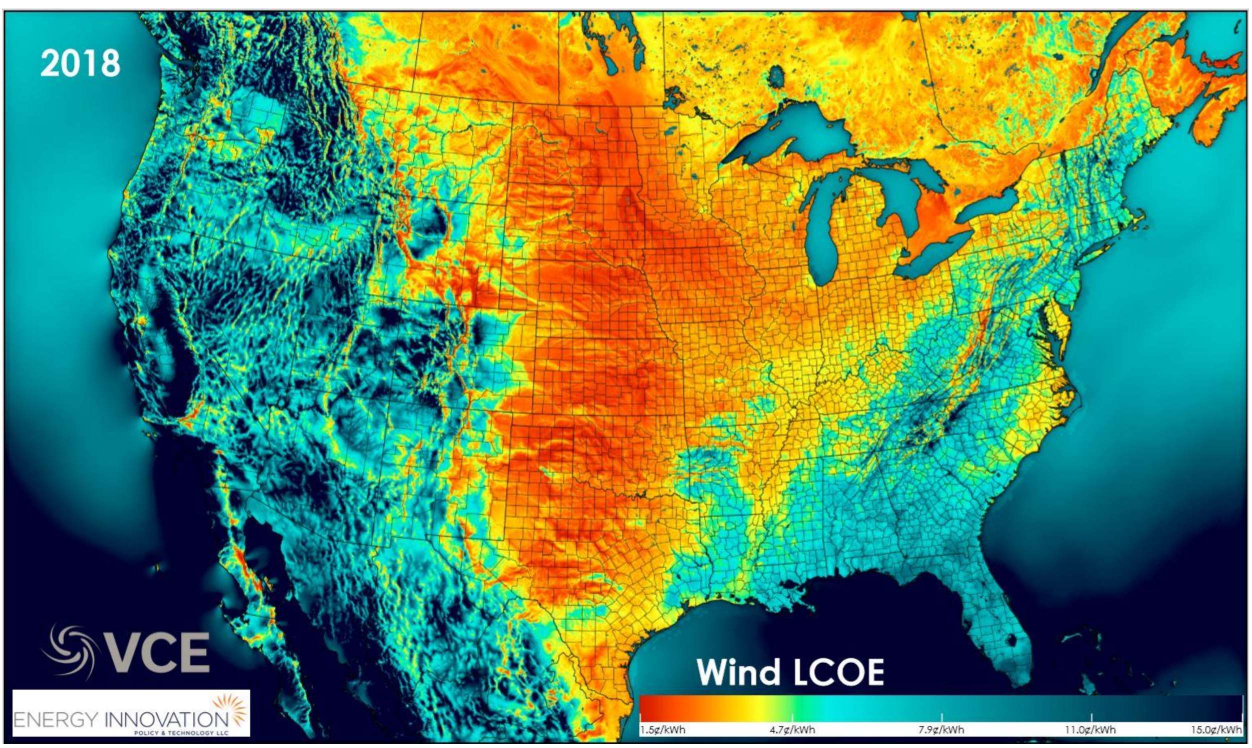
The MCOE combines fuel and variable costs based on the operation and maintenance (O&M) of power plants, as well as the fixed O&M and the ongoing capital spending for pollution controls and other upgrades to the power plant. Those later fixed costs were converted to $/MWh, using plant-specific capacity factors. For plants in regular use (capacity factors over 33%) this analysis shows a wide range of MCOEs, from $25 / MWh to $104 / MWh. For smaller capacity factors, the MCOE values quickly climb even higher, as O&M expenses are spread over fewer and fewer hours, and efficiency plummets. High-resolution images of the maps showing coal operational costs compared new renewables.

[11] "Annual Technology Baseline," National Renewable Energy Laboratory, August 2018, https://atb.nrel.gov/. These estimates are justifiable due to cost declines today that indicate we're already reaching the NREL ATB mid-case numbers. 2018-vintage contracts for wind and solar are available from Level 10.

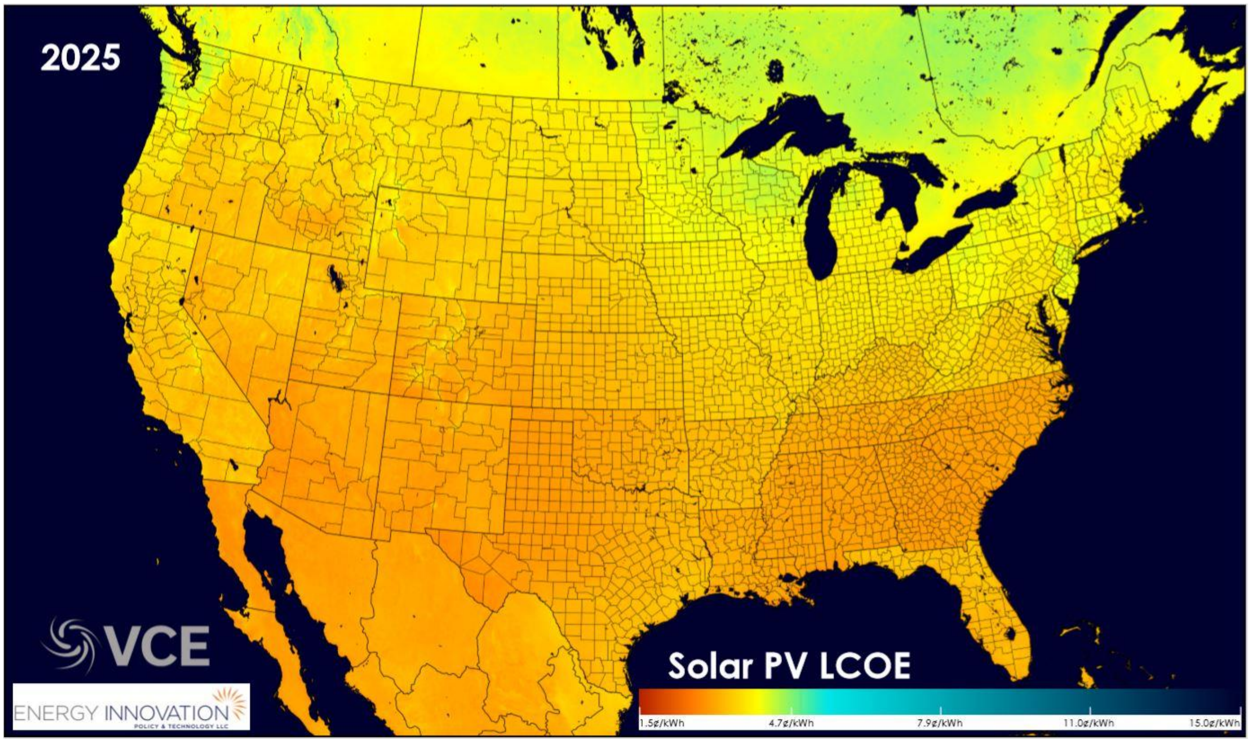
[12] "Renewable Electricity Production Tax Credit (PTC)," United States Department of Energy, https://www.energy.gov/savings/renewable-electricity-production-tax-credit-ptc



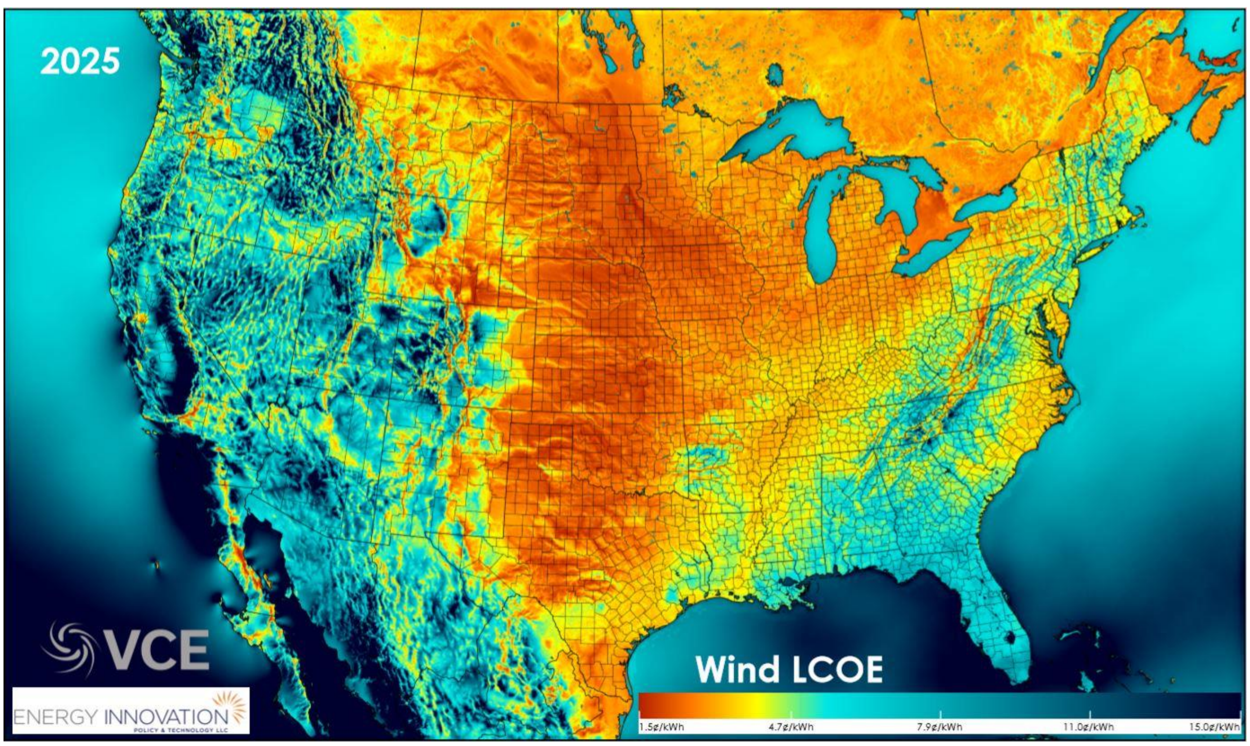
Map of the levelized cost of energy for U.S. solar photovoltaic projects in 2018 using VCE dataset



Map of the levelized cost of energy for U.S. wind projects in 2018 using VCE dataset



Map of the levelized cost of energy for U.S. solar photovoltaic projects in 2025 using VCE dataset



Map of the levelized cost of energy for U.S. wind projects in 2025 using VCE dataset

The coal plant dataset provides additional information that can be used for further analysis. First, it includes location and installed capacity of each coal-fired power plant. Second, it includes the heat rates, capacity factors, ages, and plant names for ease of reference on the MCOE construction.

COAL TO RENEWABLES COST CROSSOVER

In order to compare the costs of building new renewables with the ongoing costs of running coal plants, this report combines the two datasets above to present simplified cost crossover math. Examining each coal-fired power plant in the dataset, VCE determined how nearby wind and solar could be used to replace that coal plant. To determine the risk profile of the coal generation to wind and solar replacement, we compared the MCOE of the coal-fired power plant with the LCOE of the total wind or solar output required to replace all the coal megawatt hours (VCE looked only at either all wind or all solar replacement).

The VCE algorithm logic is explained in Appendix C. In short, it replaces all the MWhs generated from each coal plant annually using local wind or local solar in a search pattern for sites that are available for deployment[13] steadily increasing in distance. The maximum distance the algorithm required to identify replacement wind or solar resources for any given power plant was 35 miles, with a resulting average of 16 miles; these are very local replacements on the scale of the national maps being presented with this report. Sites deemed unsuitable for development by the VCE site screening algorithm were excluded from the assessment. The algorithm did not look further afield for cheaper combinations of distant resources and transmission. Its output is strictly the LCOE of local wind or solar required to replace each coal plant, transformed into a percentage difference between the MCOE of the existing coal generation and new local wind and solar.

Any plant with a negative percentage difference for solar or wind replacement was deemed at risk, and "*substantially at risk*" if the differential was less than -25% with local resources.

The quantity of energy replacement is only compared in terms of annual generation and doesn't capture the time-based value of energy and grid services from a dispatchable (if not always so flexible) coal plant. Further useful analysis could compare a coal plant with a "virtual power plant," combining wind, solar, storage and demand-side resources to more closely mimic or improve on the dispatch of the coal plant and reliability services.

But, as mentioned above, while the VCE analysis includes the cost of interconnecting new local wind and solar, the search algorithm does not look further afield for even cheaper resources once it has replaced the required MWhs. In Colorado, for example, no coal plant is at risk from local wind in this analysis, but we know that wind in the eastern part of the state easily competes

[13] Suitability is determined using the VCE site screening algorithms that remove all protected areas, urban areas, critical flora and fauna, as well as topographical constraints on construction. Further, the algorithm provides buffer space for habitation and other land uses around the potential resource candidate technology.

with coal and is accessible via in-state transmission. In light of these factors, cost crossover would likely be more common if transmission expansion were taken into account.

FINDINGS – COAL AT RISK NUMBERS

Using the cost crossover algorithm, VCE determined that in 2018 more than 49 GW of coal were substantially at risk from local wind and more than 69 GW are substantially at risk from local solar, meaning they could be replaced with local renewable energy resources at least 25 percent cheaper than the running costs of the coal.

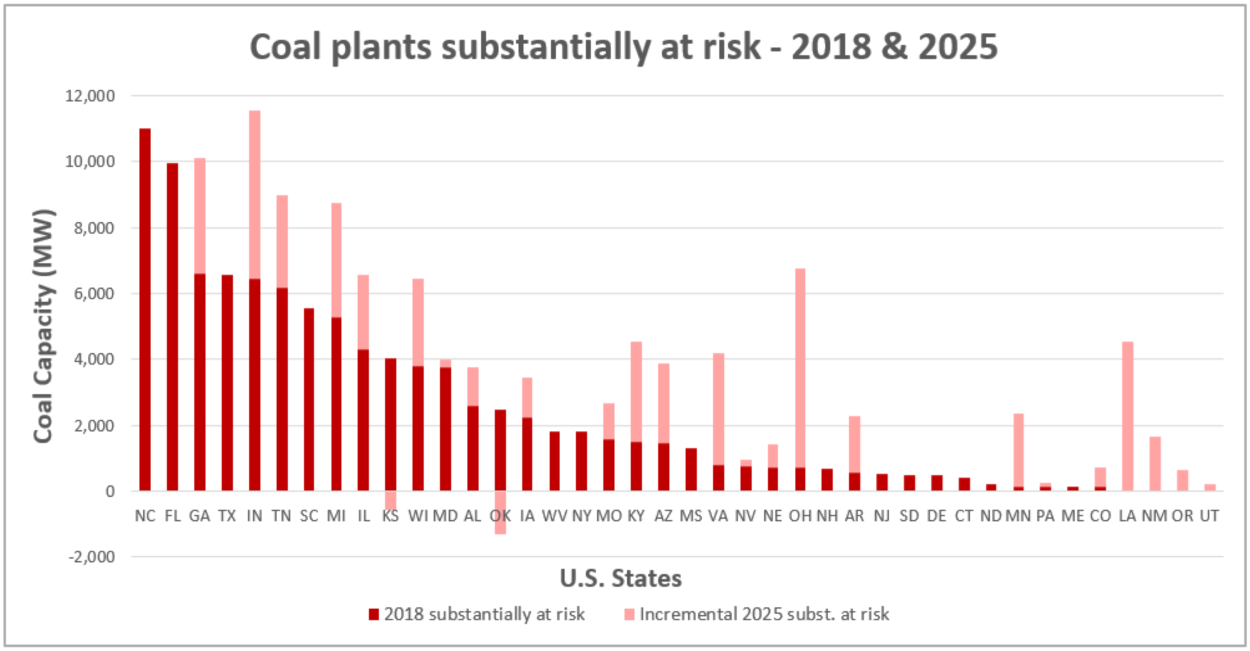
By 2025, local wind and solar could respectively replace roughly 76 GW and 111 GW of coal generation at 25 percent lower costs than running the coal-fired power plants.[14] Combining the wind and solar datasets, VCE finds that 211 GW of coal capacity, or 74 percent, is at risk with **94 GW substantially at risk** from 2018 possible local wind and solar. Assuming the NREL lower cost technology baseline case for 2025, substantially at-risk coal increases to 140 GW (with sunset tax support), or almost half of the U.S. fleet.

MW	RE Cost	Wind (2018)	Solar (2018)	Wind (2025)	Solar (2025)	Combined (2018)	Combined (2025)
Coal substantially at risk	*>25% less than coal*	*49,165*	*69,117*	*75,778*	*111,077*	*93,812*	*140,073*
Coal at risk	*0-25% less than coal*	*118,085*	*178,871*	*167,201*	*229,001*	*210,842*	*246,306*
Coal potentially at risk	*0-25% more than coal*	*168,563*	*107,777*	*119,447*	*57,647*	*75,806*	*40,342*
Coal deemed safe	*>25% more than coal*	*101,792*	*49,620*	*46,289*	*15,706*	*21,608*	*7,866*

We also report the substantially at-risk coal by state, as this is often the most relevant jurisdiction for the future of any at-risk coal plant[15]:

[14] Using NREL ATB low.

[15] There are two states where the MW of coal in the substantially at-risk categories falls from 2018 to 2025. This is because those plants are right on the cusp (-25%) of that category and a slight increase in local costs, due to PTC sunset causes them to move the less risky category.



Note that many Midwestern states see a significant increase in substantially at-risk coal by 2025, reflecting the continuing drop in price for local solar and the high marginal costs of these coal plants. Solar costs have less geographic variation and are therefore projected to become locally accessible in more places than wind, but Midwestern states could also readily access rich wind resources to the west with more transmission.

The sharpest patterns are regional. Almost all coal plants in the PJM footprint are at risk to coal replacement on a straight energy value comparison by 2025. Of course, coal plants in PJM garner a large fraction of their revenue from capacity markets that are unfriendly to solar[16] (in part because they make no allowances for seasonal performance or time-of-day value). This keeps them afloat, with a huge opportunity cost to customers. Another strong regional trend is in the Southeast, where almost all coal plants are substantially at risk to replacement by local solar in 2025 (solar energy is often available there at half the cost of coal power using the NREL lowest-cost scenario). The trend is so strong that it is hard to imagine Southeastern utilities not relying heavily on solar and complementary load shifting resources to replace the coal and save customers money.

The overall conclusion is clear: Much of the U.S. coal fleet is simply becoming uneconomic and analysts, utilities, other stakeholders, regulators, and policymakers need to take a critical look at

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[16] Jacob Mays, David Morton, and Richard P. O'Neill, "Asymmetric Risk and Fuel Neutrality in Capacity Markets," United States Association for Energy Economics Working Paper No. 19-385 (February 8, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3330932; Robbie Orvis and Eric Gimon, "The State of Wholesale Power Markets: What's Wrong With Proposed Changes in Eastern RTOs?" Utility Dive, June 20, 2017, https://www.utilitydive.com/news/the-state-of-wholesale-power-markets-whats-wrong-with-proposed-changes-in/445417/.

each and every coal plant in their jurisdiction.

In this analysis, wind and solar replace all coal-fired generation solely on an annual basis, but as previously stated, a limitation of this analysis is that replacing annual generation does not capture coal generation dispatch timing. Despite its notorious inflexibility, coal is mostly dispatchable, while wind and solar are variable sources of energy whose output, even in aggregate, does not necessarily match demand. But so-called "baseload" coal economics typically require high capacity factors, limiting their use as flexibility resources (high capacity factors require avoiding frequent ramping up and down) and creating a premium for what flexibility they offer, as consumers must pay the costs of running higher-cost energy sources year-round to access that flexibility.

The wider the gap becomes between the marginal economics of coal versus wind and solar, the more coal plants will have to depend on their perceived capacity value to recover costs. Their capacity factors may drop even more, widening the gap, and opening a window for dedicated resources like demand response, storage, and existing flexible resources to fill their niche.

DISCUSSION

This report suggests a sunset scenario for coal power. Not all plants will retire immediately —a steady flow of exits is more likely, especially where capacity markets and monopoly utilities support uneconomic coal generation at the expense of new renewables — but all stakeholders must prepare for the looming economic reality.

The first step for merchant owners, utilities, regulators, and other stakeholders is taking a hard look at coal retirement. For regulated utility assets, integrated resource plans (IRP) and other long-term planning analytical efforts should always include coal retirement scenarios. Indiana utility NIPSCO has shown how smart analysis can flip planning directions: Their most recent planning effort recommended replacing all their coal in the next decade with renewable energy, including wind and solar, along with battery storage[17]. Consumer advocates elsewhere should be asking whether coal plants receiving state-regulated cost recovery but operating in transparent competitive regional energy markets[18] should be allowed to run at loss to the detriment of consumers' pocketbooks[19].

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[17] Andrew Steele, "NIPSCO Plan Would Eliminate Coal-Fired Electricity Generation Within 10 Years," *The Times of Northwest Indiana*, September 19, 2018, https://www.nwitimes.com/business/local/nipsco-plan-would-eliminate-coal-fired-electricity-generation-within-years/article_269a1f6b-1a24-5180-976d-27a474d8ee47.html.

[18] United States Department of Energy, *Principles for Increasing the Accessibility and Transparency of Power System Planning*, January 2017, https://www.energy.gov/sites/prod/files/2017/01/f34/Principles%20for%20Increasing%20the%20Accessibility%20and%20Transparency%20of%20Power%20System%20Planning.pdf.

[19] Joseph Daniel, "The Coal Bailout Nobody is Talking About," *Union of Concerned Scientists* (blog), September 24, 2018, https://blog.ucsusa.org/joseph-daniel/the-coal-bailout-nobody-is-talking-about. A virtual power plant (VPP) is a cloud-based distributed power plant that aggregates the capacities of heterogeneous distributed energy

Consumer advocates faced with utility inertia, environmental advocates concerned about unpriced coal externalities, and advanced energy solutions providers eager to open opportunities can push back against reliability or dispatchability arguments by comparing the economics of any single coal plant with a combination of local (or distant but easily accessible) renewables with complementary demand-side and storage resources, or virtual power plants (VPP)[20]. If a VPP drop-in replacement also proves more economic than an at-risk coal plant, it can provide an estimate of the *minimum* savings available from coal plant retirement.

A more holistic approach leveraging other existing assets on the grid can prove to be even cheaper for integrating low-cost renewables. For example, a VCE study[21] showed how Colorado could replace all its aging coal plants with a mix of wind, solar, natural gas, and storage to save the state's electric customers more than $250 million annually without affecting reliability. This example is especially notable in the context of this report, because Colorado appears on the tail end of states with coal plants at risk from renewables within 35 miles.

Because coal plants in the central and eastern part of Colorado are most economically replaced with cheap wind from the eastern part of the state, not with local resources (although solar does start becoming a local option by 2025), our cost crossover analysis does not flag many of these plants as at risk (see 2025 LCOE wind map). In fact, this is true for most of the West, where high-quality wind resources in the $15 – 25 / MWh range are often only accessible through large transmission projects. Understanding the geographic dimensions of renewable costs – the opportunities visible in our maps – and proper modeling are therefore key to planning analysis and decision-making.

For coal plants in a vertically integrated jurisdiction like Colorado, and in hybrid setups where coal plants participate in wholesale markets but long-term costs are covered by ratepayers (e.g. many states in Southwest Power Pool and Midcontinent Independent System Operator), it is also useful to look not just at the MCOE of a given coal plant, but also at the remaining balance of long-term costs. Captive customers are on the hook for these costs. If an at-risk coal plant retires but is not paid off, significant incremental savings await ratepayers, especially if the remaining amortization balance can be refinanced at a lower cost than typical utility rates of return[22].

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resources (DERs) for the purposes of enhancing power generation, as well as trading or selling power on the electricity market.

[20] Mark Dyson, Alexander Engel, and Jamil Farbes, *The Economics of Clean Energy Portfolios*, Rocky Mountain Institute, 2018, https://rmi.org/wp-content/uploads/2018/05/RMI_Economics_Of_Clean_Energy_Portfolios_2018.pdf.

[21] Vibrant Clean Energy, "New Study Finds That Replacing Aging Coal Plants With Wind and Solar Saves Colorado $2.5 Billion by 2040 While Sharply Slashing Emissions," January 8, 2019, https://www.vibrantcleanenergy.com/wp-content/uploads/2019/01/CEI-VCE_CO_CoalPlantRetireStudy(CRS).pdf.

[22] "Financial Transition," America's Power Plan, December 2018, https://americaspowerplan.com/power-transformation-solutions/financial-transition/.

When evaluating coal replacement by other long-term contracts, Colorado offers another interesting example because of its competitive IRP process where potential suppliers bid against each other to meet future needs. This kind of bidding transparently surfaced cost numbers that revealed some of the first signs that cost crossover was possible.

In competitive markets run by Independent System Operators (ISOs), cost crossover analysis indicates where markets are likely out of balance with current economic realities. Obviously, if plant owners are taking all the risk and wholesale prices remain below coal plant MCOE, coal plants will bow to economic pressure and retire. For example, in 2018, Texas' ERCOT system had at least five coal plants close or announce plans to close.[23] In PJM's most recent look at incorporating ambitious fractions of renewables[24], the largest amounts of solar generation considered are nowhere near the hundreds of terawatt-hours of coal to solar replacement implied in this report's analysis. With proper planning and more technology-agnostic rules, tremendous value can be unlocked for customers served by ISOs and utilities.

CONCLUSION

Coal is a dirty and expensive way to generate electricity. The National Academies estimated that in 2005, U.S. coal generation alone caused at least $62 billion in non-climate related damages.[25] Coal's remaining rationale was that it was cheap if externalities weren't included, but even that rationale is vanishing. Our report shows that coal is increasingly uneconomic against *new* local wind and solar resources.

The next refuge for those with an economic stake in coal generation is reliability, or claims that the grid cannot run reliably without it. This report cannot directly address that contention, but more holistic studies like the VCE Colorado or Minnesota studies[26] or the NREL[27] renewable integration studies do undercut this point.

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[23] Miranda Green, "Texas Coal Plant Announces Plans to Shut Down," *The Hill*, September 25, 2018, https://thehill.com/policy/energy-environment/408369-texas-based-coal-fired-plant-announces-retirement.

[24] "Renewable Integration Study Reports," PJM Interconnection, https://www.pjm.com/committees-and-groups/subcommittees/irs/pris.aspx.

[25] The National Academies, *Hidden Costs of Energy*, 2009, https://www.nap.edu/resource/12794/Hidden_Costs_Key_Findings_final.pdf.

[26] Vibrant Clean Energy, "New Study Finds That Replacing Aging Coal Plants With Wind and Solar Saves Colorado $2.5 Billion by 2040 While Sharply Slashing Emissions," January 8, 2019, https://www.vibrantcleanenergy.com/wp-content/uploads/2019/01/CEI-VCE_CO_CoalPlantRetireStudy(CRS).pdf; Vibrant Clean Energy, Minnesota's Smarter Grid, July 31, 2018, https://www.mcknight.org/wp-content/uploads/Minnesotas-SmarterGrid_FullReport_NewFormat.pdf.

[27] Joshua Novacheck, Greg Brinkman, and Gian Porro, *Operational Analysis of the Eastern Interconnection at Very High Renewable Penetrations*, National Renewable Energy Laboratory, September 2018, https://www.nrel.gov/docs/fy18osti/71465.pdf; "Renewable Electricity Futures Study," National Renewable Energy Laboratory, https://www.nrel.gov/analysis/re-futures.html; "Interconnections Seam Study," National Renewable Energy Laboratory, https://www.nrel.gov/analysis/seams.html; "Eastern Renewable Generation Integration Study," National Renewable Energy Laboratory, https://www.nrel.gov/grid/ergis.html.

Other resources will be required to complement wind and solar and provide essential reliability services, but the increasingly attractive relative value proposition for the raw energy available from wind and solar versus more expensive coal generation can generate more and more money to directly address grid challenges. Steep declines in costs for resources like battery storage will stretch that money even more. Furthermore, it is becoming clear that wind and solar can become an asset rather than a liability when it comes to essential reliability services due to their highly responsive power electronics.[28]

Large majorities of Americans support increasing the use of solar and wind energy in their states[29]. The data in this report provide an economic rationale for a coal phase-out in the next decade led by wind and solar, happening a lot quicker than most had imagined. It's time to get on with the coal-to-clean transition.

[28] Energy and Environmental Economics, Inc., *Investigating the Economic Value of Flexible Solar Power Plant Operation*, October 2018, https://www.ethree.com/wp-content/uploads/2018/10/Investigating-the-Economic-Value-of-Flexible-Solar-Power-Plant-Operation.pdf.

[29] "Findings From the Fall 2018 NSEE," Gerald R. Ford School of Public Policy, http://closup.umich.edu/national-surveys-on-energy-and-environment/nsee-2018-fall/renewables.php.

APPENDIX A

SOLAR PV POWER DATASET

To create a high resolution levelized cost of electricity (LCOE) dataset a power dataset is required. Vibrant Clean Energy, LLC (VCE) has created such a power dataset for solar PV across the United States. The power dataset is at a geographic resolution of three km and a temporal resolution of five minutes. The solar PV power dataset spans five calendar years.

To construct the solar PV power dataset, VCE acquired the full three-dimensional (native) fields of the National Oceanic and Atmospheric Administration (NOAA) High Resolution Rapid Refresh (HRRR). VCE has continued to expand the only 3-D archive of the HRRR for both assimilation hours and forecast out to 36 hours. The numerical weather prediction (NWP) model data from NOAA is crucial because it includes 20 - 50,000 observations collected and quality controlled by the National Weather Service (NWS). The observations include ground-based measurements, satellites, aircraft, radar, balloon launches, and more. In addition, VCE acquired the GOES-East and GOES-West Satellite telemetry for the visible band, three Infrared bands, and the water vapor band. The temporal resolution of the satellite data is 15-minutes. The satellite dataset spans the same time period as the NOAA HRRR dataset. The satellite dataset has been collected because it is well understood that NWP are poorer at cloud resolving than satellites in terms of thickness and dispersion. Further, the dual satellite imagery facilitates stereographic projections of the clouds for computing the shading, reflection and absorption of solar irradiance in many grid cells. Finally, VCE collected the NOAA SURFRAD and SOLRAD high-precision ground-based measurements for solar irradiance. This will be used in the deep-learning AI algorithm contained in VCE's Solar Irradiance Model (SIM).

Not every variable in the HRRR dataset is used for the solar PV power estimates. For the proprietary algorithm created by VCE, the Solar Power Model (SPM), we extract: the wind speed at two meters, the incoming shortwave radiation, the incoming longwave radiation, the outgoing shortwave radiation, the outgoing longwave radiation, the clouds in the column above the ground resource sites, the hydrometeors in the column, the temperature, the clouds and hydrometeors in the beam direction, and the estimated aerosols.

In addition to collecting data from the HRRR, GOES, SURFRAD, and SOLRAD, VCE must compute some critical variables that have a significant influence on solar irradiance: The Earth-Sun distance, the declination angle, the hour angle, the azimuth angle, the zenith angle for every single site across the United States. An important addition is the Equation of Time that can disrupt accuracy at five-minute resolution if not included.

The HRRR dataset is at hourly resolution. It is at this stage that we convert the hourly data into five-minute data. We do this using the tendencies (derivatives) within the HRRR model as well as statistical methods to create a continuous function between hours. The five-minute resolution allows use of cloud scattering and other variables in the HRRR that can be useful to determining solar PV power at shorter-time periods than the hourly data.

The procedure to create the datasets is somewhat similar to that described in Clack, 2017[30]. We recap the major points here for completeness.

The first part of the procedure is to create the Direct Normal Irradiance (DNI), the Diffuse Horizontal Irradiance (DHI), and the Global Horizontal Irradiance (GHI). We require all components because the solar panels respond differently to the DNI and DHI; particularly with heating of the panels and the photoelectric effect. The SIM trains the learning algorithm (AI) with the ground-based observations from the SOLRAD and SURFRAD sites. These are considered the "truth" with their measurement errors incorporated. The GOES and NWP datasets are the components to be combined to produce the ground-based measurements. Of course, a small subset is held back from the training algorithm to validate the approach. The approach begins with a shallow-learning sequence (as in Clack, 2017); but then continues with deeper learning that recombines different variables in unconventional ways to increase the precision of the estimates. There are ~630,000 observations to train upon. The training is performed repeatedly with different data levels available. For example, one satellite only available; part of a satellite missing, all satellites missing, some hydrometeors missing, etc. It is important to note that the nearest one-minute average of the ground-based observation is used for the five-minute estimates. We combine errors of measurements and five-minute variance for the observations. This is a deliberate choice; the SIM is comparing a point to a grid cell average. We do not want to over-fit the learning. Note that the SURFRAD and SOLRAD sites span the U.S. and are in different urban/non-urban environments.

The conclusion of the SIM is where the deep learning algorithm applies the computed coefficients to all sites across the U.S. for all five-minute time periods. The outputs are GHI, DNI, DHI, hour angle, azimuth angle, zenith angle, declination angle, clouds, aerosols, temperature, and wind speed at two meters.

Once the SIM outputs are created, the procedure moves to the second stage, which is the SPM. The SPM include parameters for different solar PV types. The standard used is mono-crystalline. The SPM computes the power estimates based on the SIM outputs, the angle of the panels, the shading, the tracking assumed, and the terrain / elevation. The SIM outputs include temperature and wind speeds, that allows computation of the heating of the panels that influences the power production vastly. The Invert Loading Ratio (ILR) is assumed to be 1.2. The SPM has the ability to perform the computations with any level of ILR; but this would add too many degrees of freedom if it was not consistent across the U.S.

The SPM computes the instantaneous CF for each three-km site for each five-minute time step. The power can be above 100 percent rated power because of temperature dependency, cloud brightening, Inverter loading, and snow cover. The SPM is limited to only allowing 130 percent of

[30] Christopher T. M. Clack, "Modeling Solar Irradiance and Solar PV Power Output to Create a Resource Assessment Using Linear Multiple Multivariate Regression," *Journal of Applied Meteorology and Climatology*, (January 2017): 109-125, https://journals.ametsoc.org/doi/pdf/10.1175/JAMC-D-16-0175.1.

the rated capacity. This is to avoid overloading the inverters. The rated power is defined by the solar panels installed. This is because for costs later, we use the cost for installing at 1.0 ILR, so we require consistent definitions.

The solar PV power dataset is the final output of SPM. Currently, the dataset covers multiple tilts for fixed PV, one-axis tracking (North-South facing, tilted at latitude) and two-axis tracking. It does also include rooftop solar PV estimates, which is based on roof space, average tilt of roof, shading, and pitch of roof in each three-km grid cell. The one-axis tracking is the most widely adopted in the U.S., but the other versions allow comparison for production and optimal siting at a later date. For example, northern states would benefit from two-Axis tracking for higher solar production in the winter months, which would offset the additional cost of construction. However, the far south could use fixed axis tilted at an optimal angle and save on having tracker technologies. A short visualization of the solar PV dataset is available online.[31]

COSTS AND INCENTIVES

Once the solar PV power dataset is created, we can start to apply costs to the resource sites. In the previous section, we have only dealt with the physics of the solar irradiance and power; and not how economics alters the picture for site preference. To apply costs, we use the National Renewable Energy Laboratory (NREL) Annual Technology Baseline (ATB) 2018. The NREL ATB 2018 provide costs for numerous years and technologies. We have chosen to use the 2018 costs along with the 2025 (low and mid) projection. The solar cost is referenced to the one-axis tracking for each site across the U.S.

The economic life of the solar PV plant is estimated to be 25 years. The Weighted Average Cost of Capital is assumed to be 5.87 percent (real). The fixed and variable costs are also pulled from the NREL ATB 2018.

The federal incentives of the Production Tax Credit (PTC) and Investment Tax Credit (ITC) are applied with their current sunset dates. Only the ITC is applied to the solar sites.

The U.S. is extremely diverse in its costs for labor, materials and permitting. The algorithm used for the modeling includes a component that applies state-level multipliers to the cost of the solar PV construction. They are applied at the state-level because of data availability. The multipliers range from 87.5 percent to 105.0 percent. Further there is cost multipliers for the different technologies. For the one-axis tracker there is a 15 percent premium for building the tracker system compared with the fixed panels, with no tilt.

TRANSMISSION CONSIDERATIONS

The VCE WIS:dom optimization model includes detailed transmission datasets. The transmission datasets include the transmission lines, their voltage, the transmission substations and their capacities. For each three-km site from the solar PV power dataset, a geodesic is computed to

[31] "Solar Power For Day 10 of 2014 – Coincident With Winds," Christopher Clack, Youtube video (May 23, 2018), https://www.youtube.com/watch?v=d22m0KHy5Fs.

the nearest substation. The cost of the solar resource site is increased by the cost to construct the transmission line to the nearest substation. Further, if the WIS:dom model determines the substation is close to capacity, the solar site will incur a cost to upgrade the transmission substation as well. This is relaxed for the 2025 versions, because the grid topology is likely to change by that date.

LCOE MAPS AND DATA LINKS

With the costs and power datasets completed, the final step is to produce the LCOE mapping. The power dataset is converted to capacity factors for each three-km resource site. The capacity factor is combined with the costs to produce the LCOE. Essentially, total costs (capital, fixed, transmission, multipliers) divided by potential generation (CF * Size * 8760). We allowed only one-axis tracking tilted at latitude and orientated North-South.

VCE has created NetCDF files that include the LCOE data for 2018, 2025 Low, and 2025 Mid. Further, VCE has visualized the LCOE data in PDF. The images allow easy zoom capabilities into regions of the United States to be used by all. The data files allow more precise analysis using the LCOE mapping.

The location of the data files is:

https://www.vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/SolarLCOE_Data.zip

The locations of the images are:

https://vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/SolarPVLCOEMap_2018_cobrand_samescale.pdf

https://vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/SolarPVLCOEMap_2025L_cobrand_samescale.pdf

https://vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/SolarPVLCOEMap_2025M_cobrand_samescale.pdf

APPENDIX B

WIND POWER DATASET

To create a high resolution levelized cost of electricity (LCOE) dataset a power dataset is required. Vibrant Clean Energy, LLC has created such a power dataset for wind across the United States. The power dataset is at a geographic resolution of three km and a temporal resolution of five minutes. The wind power dataset spans five calendar years.

To construct the wind power dataset, VCE acquired the full three-dimensional (native) fields of the National Oceanic and Atmospheric Administration (NOAA) High Resolution Rapid Refresh (HRRR). VCE has continued to expand the only 3-D archive of the HRRR for both assimilation hours and forecast out to 36 hours. The numerical weather prediction (NWP) model data from NOAA is crucial because it includes 20 - 50,000 observations collected and quality controlled by the National Weather Service (NWS). The observations include ground-based measurements, satellites, aircraft, radar, balloon launches, and more.

Not every variable in the HRRR dataset are used for the wind power estimates. For the proprietary algorithm created by VCE, the Wind Power Model (WPM), we extract: he wind speeds from 20 m to 240 m above ground level in 10 meter increments, the wind direction at each height, the air density at each height, turbulent kinetic energy at each height, temperature at each height, hydrometeors at each height, and the clouds at each height. The HRRR model is in hybrid-sigma coordinates and these are interpolated to height above ground level using cubic spline interpolation.

The HRRR dataset is at hourly resolution. It is at this stage that we convert the hourly data into five-minute data. We do this using the tendencies (derivatives) within the HRRR model as well as statistical methods to create a continuous function between hours. The five-minute resolution allows use of wind gusts and other variables in the HRRR that can be useful to determining wind power at shorter-time periods than the hourly data.

The procedure to create the datasets is somewhat similar to that described in Clack et al., 2016[32] and Choukulkar et al., 2016[33]. We recap the major points here for completeness.

The first part to convert weather variables to power estimates is to create the Rotor Equivalent Wind Speed (REWS). The REWS is a scalar value that estimate the average wind speed across the entire rotor swept area. In Clack et al., 2016 the methods were expanded to include NWP models and the full power equation; which accounts for the discretization of the wind speed and derivatives for NWP. Further, in Choukulkar et al., 2016, the method was further expanded to

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[32] Christopher T. M. Clack, et al., "Demonstrating The Effect of Vertical and Directional Shear for Resource Mapping of Wind Power," *Wind Energy* 19, (November 2015): 1687-1697, https://www.vibrantcleanenergy.com/wp-content/uploads/2016/11/Demonstrating_the_effect_of_vertical_and.pdf.

[33] Aditya Choukulkar, et al., "A New Formulation for Rotor Equivalent Wind Speed for Wind Resource Assessment and Wind Power Forecasting," *Wind Energy* 19, (September 2015): 1439-1452, https://www.vibrantcleanenergy.com/wp-content/uploads/2016/11/Choukulkar_et_al-2016-Wind_Energy.pdf

include the turbulent kinetic energy influence on the power equations. The REWS formulation can be found in those peer-reviewed papers. The REWS also takes into account the sheer and veer across the rotor swept area. A similar procedure is required for the temperature, clouds, and air density. Two video visualizations of the wind data set can be found online[34,35].

Once the REWS and other variables are created for the wind power dataset, the power estimates must be constructed. This is done using the wind power equations from Clack et al., 2016 and Choukulkar et al., 2016. The WPM uses a combination of wind turbines from each wind resource class to create a generic wind turbine for each. The generic wind turbine has a coefficient of power curve that is a function (rather than a data table). The coefficient of power (or C_P) is the efficiency of the wind turbine to extract power from the wind. It is used within the power equation. A more common tool is the power curve; however, this is more limited because it does not allow changes in air density, and is less sensitive to the cube of the wind speed (when using the REWS formulation). This is particularly important when considering the full power equation and turbulent kinetic energy.

Once the WPM has completed there is wind power for the optimal turbine class for each three-km across the United states for each five-minute interval for a five-year period. A visualization of the wind power (at 80m AGL) is available online.[36] The current iteration of the wind power dataset has power for 80 meters, 100 meters, 120 meters, 140 meters, and 160 meters. It includes terrestrial and offshore wind resources.

COSTS AND INCENTIVES

Once the wind power dataset is created, we can start to apply costs to the resource sites. In the previous section, we have only dealt with the physics of the wind; and not how economics alters the picture for site preference. To apply costs, we use the National Renewable Energy Laboratory (NREL) Annual Technology Baseline (ATB) 2018. The NREL ATB 2018 provide costs for numerous years and technologies. We have chosen to use the 2018 costs along with the 2025 (low and mid) projection. The wind cost is referenced to the optimal type for each site across the United States – including for offshore wind.

The economic life of the wind turbines is estimated to be 30 years for terrestrial and 25 years for offshore. The Weighted Average Cost of Capital is assumed to be 5.87 percent (real). The fixed and variable costs are also pulled from the NREL ATB 2018.

The federal incentives of the Production Tax Credit (PTC) and Investment Tax Credit (ITC) are applied with their current sunset dates. The PTC is applied to the terrestrial wind, while the ITC is

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[34] "10m Winds For Day 10 of 2014," Christopher Clack, Youtube Video (May 23, 2018), https://www.youtube.com/watch?v=HU_m56X0FCM.

[35] "Hurricane Arthur in 2014 – 10m Wind Speeds," Christopher Clack, Youtube video (May 8, 2018), https://www.youtube.com/watch?v=VeTGnzg4ngs.

[36] "Wind Power Across United States (4 days)," Christopher Clack, Youtube video (November 29, 2018), https://www.youtube.com/watch?v=K5kqch2QNzU.

applied to the offshore wind sites. The algorithm used for the modeling takes into account that the PTC is only applied for 10 years after construction.

The U.S. is extremely diverse in its costs for labor, materials and permitting. The algorithm used for the modeling includes a component that applies state-level multipliers to the cost of the wind construction. They are applied at the state-level because of data availability. The multipliers range from 97.5 percent to 112.5 percent.

TRANSMISSION CONSIDERATIONS

The VCE WIS:dom optimization model includes detailed transmission datasets. The transmission datasets include the transmission lines, their voltage, the transmission substations and their capacities. For each three-km site from the wind power dataset, a geodesic is computed to the nearest substation. The cost of the wind resource site is increased by the cost to construct the transmission line to the nearest substation. Further, if the WIS:dom model determines the substation is close to capacity, the wind site will incur a cost to upgrade the transmission substation as well. This is relaxed for the 2025 versions, because the grid topology is likely to change by that date.

LCOE MAPS AND DATA LINKS

With the costs and power datasets completed, the final step is to produce the LCOE mapping. The power dataset is converted to capacity factors for each three-km resource site. The capacity factor is combined with the costs to produce the LCOE. Essentially, total costs (capital, fixed, transmission, multipliers) divided by potential generation (CF * Size * 8760). We allowed up to 100 meter AGL for 2018 and up to 120 meter for 2025. The algorithm selects the optimal height for the hub based on the reduction in the LCOE. It will increase the hub height from 80 meters to 100 meters if it reduces the LCOE by more than $7.50/MWh and from 100 meters to 120 meters if it reduces the LCOE by more than $12.50/MWh. Essentially, if it chooses a 120 meter hub height, the cost of wind power is estimated to be $20/MWh cheaper than at 80 meters.

VCE has created NetCDF files that include the LCOE data along with the optimal hub heights for 2018, 2025 Low, and 2025 Mid. Further, VCE has visualized the LCOE data in PDF. The images allow easy zoom capabilities into regions of the United States to be used by all. The data files allow more precise analysis using the LCOE mapping.

The location of the data files is:

https://www.vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/WindLCOE_Data.zip

The locations of the images are:

https://vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/WindLCOEMap_2018_cobrand.pdf

https://vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/WindLCOEMap_2025L_cobrand.pdf

https://vibrantcleanenergy.com/wp-content/uploads/2019/03/LCOE-Mapping/WindLCOEMap_2025M_cobrand.pdf

APPENDIX C

COAL-FIRED POWER PLANT DATASET

A marginal cost of electricity (MCOE) dataset can be created for the existing coal-fired power plants across the United States by combining publicly available information. The data collected from FERC Form 1[37], EIA Form 860[38] and EIA Form 923[39] for the calendar year 2017. The information extracted includes the amount of fuel burned, the average heat rate of the power plants, the emission factors, the capital investments, the pollution controls, the fixed operations and maintenance costs, and the variable operations and maintenance costs.

Due to the scale of the coal dataset as well as the frequency of update for public information, inevitably there are some inconsistencies that appear in the analysis when referencing other datasets. VCE has done its best to avoid such inconsistencies in the dataset, but some will likely remain. The highest occurrence of inconsistencies will be due to: retired plants after 2017, repowering of coal plants with natural gas, naming conventions between datasets, and nameplate capacity numbers.

The coal fuel cost for the construction of the MCOE dataset is taken from the National Renewable Energy Laboratory (NREL) Annual Technology Baseline (ATB) 2018. The national average for the 2018 calendar year is used. The fuel data collected from publicly available sources for 2017 was used to adjust the national coal price to the individual power plants. If there are multiple units at a coal-fired power plant, the data was combined into a single value for the entire plant. The coal-fired power plant fuel costs are multiplied by the annual average heat rates from the publicly available data. This results in a fuel cost for each power plant in $ / MWh.

In addition to fuel costs, there are variable costs based on the operations and maintenance (O&M) of the power plant. The variable O&M was extracted from the NREL ATB 2018 and applied regionally. The values were correlated to the publicly available data. The variable O&M was constructed in $ / MWh.

The final costs included in the MCOE are the fixed O&M costs and the ongoing capital spending for pollution controls and other upgrades to the power plant. These costs are applied to the coal-fired power plants based on estimates constructed from the publicly available data. To convert these fixed costs to $ / MWh, the capacity factors for each of the power plants were utilized.

The final MCOE dataset is in $ / MWh and is the addition of the fuel costs, the variable O&M costs and the fixed costs. The combined MCOE costs are dependent on the capacity factors. The MCOE dataset was constructed to compare the cost building new wind and solar to replace the

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[37] "Form 1 – Electric Utility Annual Report," Federal Energy Regulatory Commission, https://www.ferc.gov/docs-filing/forms/form-1/data.asp.

[38] "Form EIA-860 Detailed Data With Previous Form Data," United States Energy Information Administration, https://www.eia.gov/electricity/data/eia860/.

[39] "Form EIA-923 Detailed Data With Previous Form Data," United States Energy Information Administration, https://www.eia.gov/electricity/data/eia923/.

generation from each of the coal-fired power plants. Since the MCOE is sensitive to the capacity factor of the coal-fired power plant, it should be noted that adding new wind and solar to replace the coal generation would lower the capacity factor, thereby increasing the MCOE.

The coal MCOE dataset comes with additional information that can be used for further analysis. First, the location and installed capacity of each coal-fired power plant is included. Second, the heat rates, capacity factors, age, and plant names are also included for ease of reference for the construction of the MCOE. Finally, the construction costs were estimated to compute the remaining debt for each coal-fired power plant. These debt costs were created using the publicly available data, the age of the power plants and the cumulative generation and revenue for that power plant. The debt costs were included in the LCOE, but not the MCOE.

COAL REPLACEMENT ALGORITHM

Once the coal-fired power plant dataset is created, it can be used to determine the ability for wind and solar to replace those coal plants. The LCOE for wind and solar were created previously. The LCOE calculation includes the transmission costs for interconnection, the resource potential and the localized costs for construction. The LCOE values were computed for 2018 and 2025.

The replacement of the coal generation with wind and solar is determined by comparing the MCOE of the coal-fired power plant with the LCOE of the total wind or solar required to replace all the coal megawatt hours.

The algorithm for replacing the coal generation has the following basic structure:

1. Select the coal-fired power plant to replace;
2. Find the closest wind or solar resource site;
3. Determine the generation from the wind or solar site and reduce the coal generation required to be replaced;
4. Save the installed capacity of wind or solar along with the LCOE;
5. Find the next closest wind or solar resource site;
6. Repeat steps 3–5 until the coal generation to replace becomes zero;
7. Compute the LCOE for the replacement wind or solar generation;
8. Repeat steps 1–7 until all the coal-fired power plants are replaced.

The algorithm continues until the entire generation for each coal-fired power plant is replaced with wind or solar. The output from the algorithm is the LCOE of the wind or solar required to replace the coal generation. That data is transformed into a percentage difference between the MCOE of the existing coal generation and the new wind and solar.

The algorithm could be expanded in the future to include the addition of storage and a limit to the amount of installed capacity allowed to replace the coal-fired power plants.