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Using New Marginal Emissions Data to Improve State Renewable Portfolio Standards

By **Devan Samant, Abraham Silverman,** and **Dr. Zachary Wendling**

May 2024

REPORT

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Executive Summary

The majority of US states use a renewable portfolio standard (RPS) to achieve clean energy targets. RPS programs typically set annual clean energy production levels, but they ignore the significant variations in greenhouse gas (GHG) emissions intensity of the grid at different times of the day and at different locations. Newly available locational marginal emissions (LME) data, which are collected at thousands of physical locations and updated every five minutes, provide insights into where and when the electricity sector produces the most and least GHG emissions. Incorporating LMEs into RPSs would allow states to identify and reward "high impact" clean energy production: that which replaces the dirtiest generation.

This report examines the impact that incentivizing clean energy production at high LME times and locations could have on reducing emissions in RPS programs. In five scenarios based on data from four states in the PJM grid (Illinois, New Jersey, Pennsylvania, and Virginia), the authors examine hypothetical shifts in energy production from times and geographic areas with differing clean or dirty generation mixes. The proof-of-concept exercises the authors ran found that shifting clean energy production into the three dirtiest hours of the day resulted in approximately 10% less emissions than the baseline case. Geographically shifting production to displace energy at a dirtier locale resulted in 9%–20% less emissions, depending on the LME makeup at the given location versus the baseline.

States can leverage the following LME trends to improve the effectiveness of their compliance programs:

- Grid LMEs change considerably over the course of the day. Differences in which generation resource is the marginal unit (i.e., the last unit necessary to serve load in the area) as well as congestion lead the average LME to vary by 200 pounds/megawatt-hour during the day.
- LMEs also vary by season. During the summer, peak loads typically occur in the afternoon, as cooling load drives consumption during the hottest part of the day. In the winter, peak load generally shifts into the evening as consumers return home and begin using more electricity.
- Average LMEs also differ across states, especially in winter. Illinois had the lowest average LMEs of the four states studied, but also had the largest spread in LMEs between summer and winter. This is attributable, at least in part, to the large amount of wind generation in Illinois, which typically produces more electricity in the winter months.

Introduction

Newly available locational marginal emission (LME) data provide insights into where and when the electricity sector produces greenhouse gas (GHG) emissions. LMEs are collected at thousands of physical locations, or "nodes," across the electric grid and updated on a five-minute basis as grid conditions change.[1] While real-time nodal markets have long been recognized as the "gold standard" in pricing electricity, LMEs brings the same temporal and spatial resolution principles to emissions accounting. This report provides a proof of concept for how state regulators could incorporate LME data into a state renewable portfolio standard or clean electricity standard (collectively, RPS)[2] program to reduce GHG emissions compared to a business-as-usual case.

RPS programs are currently used by 29 US states and the District of Columbia[3] to procure clean energy on behalf of consumers, making them, collectively, one of the largest programs nationally to support purchases of clean energy.[4] Today's RPS programs, however, typically treat all clean energy produced at any point during the year and at any point on the grid the same for compliance purposes. This means that an increment of clean energy production added to a relatively low-carbon grid has the same value under existing policies as an increment of clean energy production added to a relatively high-carbon grid. States could use LME data to improve the climate impact of RPS programs by "carbon indexing" or "emissions adjusting" their clean energy purchases to account for avoided GHG emissions on a more granular location and time-sensitive basis. Entities complying with the RPS would then be financially incented to procure higher impact renewable energy certificates (RECs), thereby bringing down the cost of avoided GHGs and making the RPS program more effective.[5]

This work has important implications for greenhouse gas accounting (including the ongoing Greenhouse Gas Protocol revisions),[6] calculation of the GHG impacts of hydrogen electrolzyer operations, operation of energy storage, and other similar efforts. For example, a company that today uses annual matching of clean energy production and consumption to support environmental impact claims could use LMEs to understand how its operations are affecting grid-wide GHG emissions based on where and when it is consuming power. A battery or hydrogen production facility could likewise shift their operations to minimize regional GHG emissions by charging at times and locations when the grid is cleaner. In each case, better temporal and locational data allow the entity to better quantify its emissions impact and ultimately drive clean energy investments and operations that target hours and areas with high emissions. LMEs also potentially provide a complimentary mechanism to be considered alongside hourly clean energy matching[7] programs, which net clean energy production and consumption on an hourly basis, and project- or technology-specific incentive programs.

This report begins with an overview of how state RPS programs currently work, before analyzing how incorporating LME data into them could incentivize a shift of clean energy production to a time or location that will reduce the most emissions. Based on scenarios modeled in this report that use grid operator data, the authors found that shifting new production into the dirtiest hours of the day could result in approximately 10% less GHG emissions versus the business-as-usual case. Shifting energy production from geographic areas with a relatively clean mix of generation to areas with a dirtier mix could result in up to approximately 20% emissions reductions versus the baseline.

While the maximum impact of incorporating LMEs into RPSs is hard to gauge with any accuracy, the type of market-based incentive framework demonstrated in this paper would likely improve the emissions impact of such programs over current emissions-blind REC compliance strategies.

Existing State Regulatory Regimes

States have historically turned to RPS programs to meet their clean energy goals by making "cleanness" a tradeable commodity subject to competitive market principles. While the specifics of RPS programs differ across states, mandates generally require utilities and other retail suppliers of electricity to purchase and retire a number of RECs each year. One REC represents the property rights to the environmental non-power attributes of renewable electricity generation.[8] Retirement signifies that the attributes have been claimed and cannot be resold. REC definitions and geographic qualifications are established by each state. However, most states recognize a fungible "Class I" REC product as the foundational building block of their RPS programs that represents the environmental attributes from wind, solar, and other qualifying biomass, hydropower, and landfill gas resources. Class I RECs are by far the most common REC product and are readily traded through various brokers and exchanges.[9] RPS programs typically determine the total number of RECs required to be retired by each compliance entity (typically, a load-serving entity) by applying a percentage on the total energy load in a year, and programs tend to increase that percentage steadily each year to meet long-term goals such as 100% of demand met by renewables by 2035.

RPS programs are generally viewed as effective[10] in promoting investment in clean energy facilities. But not all RECs are created equal when it comes to their GHG emissions reduction. The potential avoided emissions associated with each REC depends on the time and place that the REC is created, or "minted."[11] Clean energy produced when the overall grid is already relatively clean reduces fewer GHGs than clean energy produced when the grid is dirty, as that clean energy displaces higher emitting fossil resources. The efficacy of the RPS program also depends on whether it drives incremental investment in clean energy over and above what would have been built absent the program, which can be difficult to estimate.[12]

Under most state compliance regimes, however, RECs typically have the same market value regardless of the time and place that they are minted. While this commoditization encourages larger REC supply volumes, the downside is that there is no financial incentive to select RECs based on their potential to reduce GHGs. The advent of emissions-adjusted REC pricing[13] and the movement towards hourly matching to meet corporate sustainability standards[14] have the potential to disrupt the current compliance dynamic. Both focus on ensuring that clean energy production matches consumption. While hourly matching is intended to demonstrate that energy consumption by a particular customer (usually a large customer) is not increasing GHG emissions, LMEs may be more suitable for measuring the impact of widely distributed loads. While both approaches have merit, neither has been fully incorporated into RPS compliance standards.

Analysis Scope and Data

Our initial analysis focuses on the regional grid operated by PJM Interconnection, LLC (PJM). PJM operates the largest electric grid by energy generation in the United States, covering over 65 million customers in part or all of 13 states and the District of Columbia.[15] While the principles laid out in this paper are applicable to markets nationally, PJM was selected for the proof of concept both because the necessary data sets are available and because PJM includes states with a wide diversity of views on the importance of clean energy investment. Because political consensus on regional approaches to clean energy can be difficult to achieve, a market-based mechanism, such as carbon indexing of RECs purchased through RPS programs, has the potential to be implemented across the PJM footprint without hard-to-achieve multistate consensus. Additionally, the framework presented could be used by the two-thirds of Americans served by regional electricity markets that produce locational marginal prices (LMPs). While some adjustments would be necessary to account for differences in what data are available, how LMEs are calculated off of LMPs, and how the public can access that data, the similarities significantly outweigh the differences.

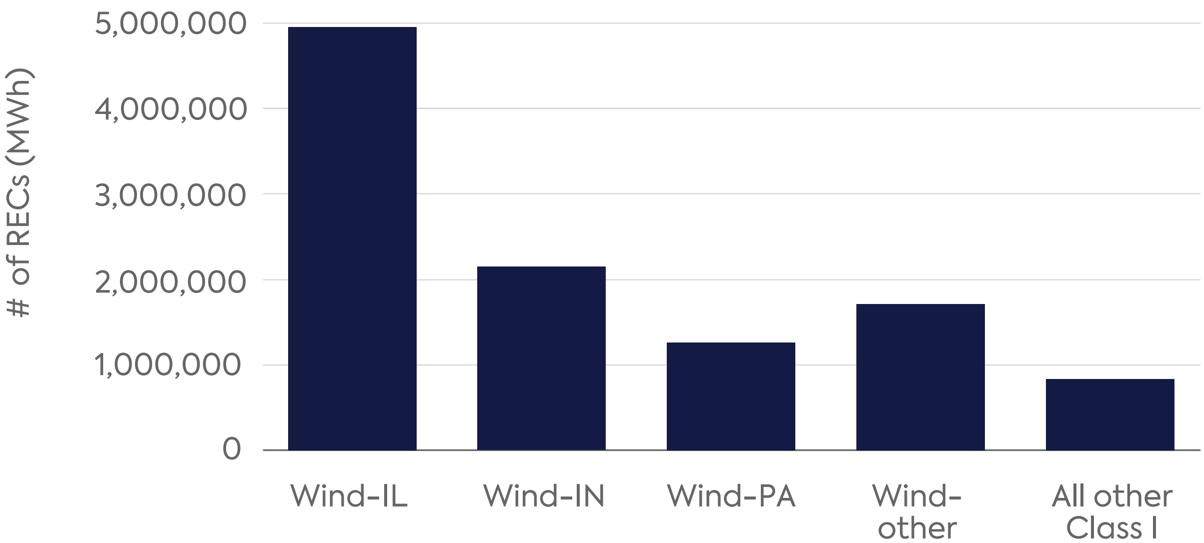
Within PJM, this report focuses on New Jersey to demonstrate the potential benefits of adopting carbon indexing. New Jersey has a long-standing RPS program with transparent data, and regulators and legislators in the state have publicly discussed incorporating carbon indexing into their RPS program designs.[16] As mentioned, the methods discussed in this paper can be applied to any state RPS program of similar structure.

Starting in September 2021, PJM began providing public access to data on marginal emissions at each of its pricing nodes.[17] As of March 2023, PJM started timestamping when a REC is minted.[18] While timestamped data are not yet usable for retired RECs, due to one-to-two year lags in REC compliance, these new data will improve the accuracy of carbon indexing of RECs in future compliance years.

Methodology

A breakdown of the approximately 11 million Class I RECs retired in New Jersey in energy year 2022 (EY2022, which covered June 2021–May 2022) to comply with the state's RPS are shown in Figure 1.[19]

Figure 1: New Jersey retired Class I RECs by type and generating location for EY2022



Note: PJM Environmental Information Services Generation Attribute Tracking System, https://gats.pjm-eis.com/GATS2/PublicReports/RPSRetiredCertificatesReportingYear/Filter.

Of the Class I RECs retired to meet New Jersey's RPS program, 46% were wind RECs generated in Illinois, as reported by PJM's Environmental Information Services (PJM EIS), the designated REC-tracking entity for New Jersey and other states in the PJM region. The remaining 54% were a mix of wind and other technologies from other parts of PJM.

In addition to the PJM EIS data, we use several datasets available through PJM's application programming interface for Python.[20] At a high level, we collect PJM wind generation profiles[21] for the region to allocate expected REC production by hour and season. We then compare PJM LMEs by node,[22] aggregated to a state level and weighted by load totals,[23] to estimate the avoided emissions associated with the retired RECs. PJM archives emissions datasets after 6–12 months and does not allow users to filter by node,[24] so this analysis also uses a nonpublic copy provided to the authors by RESurety.[25] As explained in more detail in the appendix, our method for quantifying the GHG savings associated with retired RECs starts with using actual wind profile data, by state and utility service territory, to estimate when and where wind energy was injected onto the grid, and then comparing that to the weighted zonal average LME over the same time period.

The method, as defined in the appendix, isn't perfect. It uses probability and assumptions to estimate the time and location of generation, as these pieces of information are not tagged to each REC in the underlying scope of data. Using estimates to assign time and location to renewable generation is imprecise and further limited by the granularity of the analysis where zones are used as proxies for states and 8,760 hours are used for an energy year rather than 105,120 5-minute intervals. However, PJM-EIS has already announced its intention to begin tracking REC production on an hourly basis, which will help address this limitation in the future. Another potential limitation of this study's findings is how LMEs only accurately represent small megawatt changes, so theoretical shifting of large megawatt volumes would require a rerun of PJM models to update LMEs at all nodes.

Despite any limitations, the exercises are run to highlight emissions variations and how states can make use of those. In order to capture the potential benefits of a policy change, we constructed a series of counter-factual scenarios to illustrate how GHG emissions would change if REC purchases were shifted in time or location. Specifically, we elected to look at intraday production differences across three states: Illinois, Pennsylvania, and Virginia. We elected to use Illinois as our baseline scenario, given the substantial plurality of Class I compliance RECs (46% of RECs or 5 million RECs, as shown in Figure 1) and because Illinois generally had the largest variation in LMEs. Similarly, we elected to focus on wind generation to estimate the potential for policy reforms because wind represents such a high percentage of total Class I compliance.

We examined the following scenarios:

1. **Illinois Baseline:** we estimated the GHG abatement value of RECs sourced from Illinois wind resources based on hourly LMEs from geographically relevant nodes and used historical wind generation production profiles to determine probability, per the methodology in the appendix.

2. **Illinois High LME:** we constructed a counter-factual scenario where all 5 million RECs are assumed to be minted in Illinois during only the three highest LME hours of the day each day, i.e., when the Illinois state grid is dirtiest.

3. **Illinois Low LME:** similar to the High LME concept, we assigned all 5 million RECs to the three lowest LME hours each day, i.e., when the state grid is cleanest.

4. **Pennsylvania Baseline:** we modified the adjusted LME such that it is the same scenario as the baseline but using the LMEs from Pennsylvania locations instead of Illinois, as a way to show how GHG savings might change if RECs were sourced from a different state.

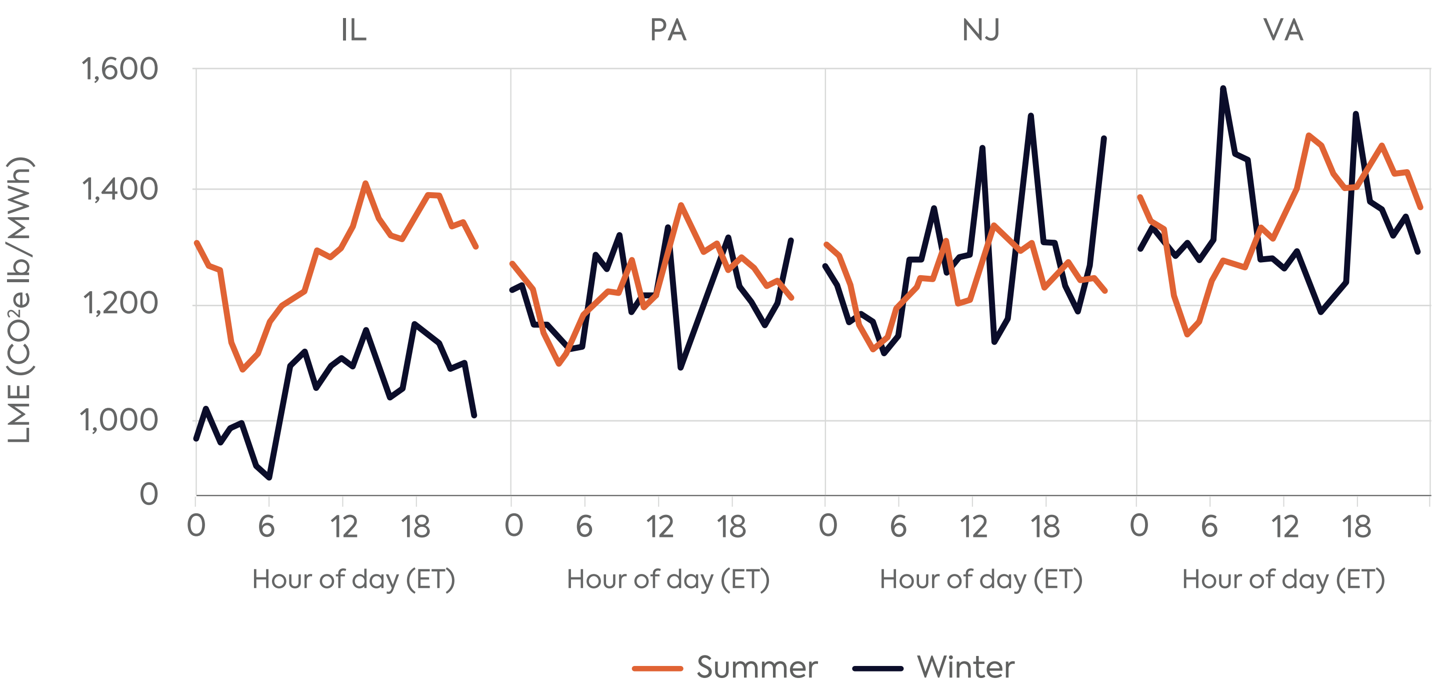
5 **Virginia Baseline:** similar to the Pennsylvania Baseline concept, we used LMEs from Virginia instead of Pennsylvania.

We recognize that these scenarios differ from today's commercial investment decisions, where a plurality of Class I RECs are produced in Illinois from wind resources. As of EY2022, Virginia was the source for less than 4% of retired Class I RECs. However, Virginia is also a popular area for solar energy development, with over 60 gigawatts of new solar and solar-plus-storage generating units put into the PJM interconnection queue between 2017 and June 2023.[26]

Results and Sensitivity

Before discussing total GHG abatement potential and scenarios, several observations and trends are apparent from average-weighted LME profiles. As shown in Figure 2, grid LMEs vary significantly by season and hour of the day. For both seasons shown, LMEs tend to follow the demand for energy across the course of the day, with minimum loads typically occurring in the middle of the night and then starting to grow as people wake up and start consuming more electricity. During the summer, peak loads typically occur in the afternoon, as cooling load drives consumption during the hottest part of the day. In the winter, peak load generally shifts into the evening as consumers return home and begin using more electricity. There were several spikes in these historical averages due to high loads on several consecutive days in EY2022 attributable to winter weather.

Figure 2: Average daily profile of LMEs for study scenario states, summer and winter

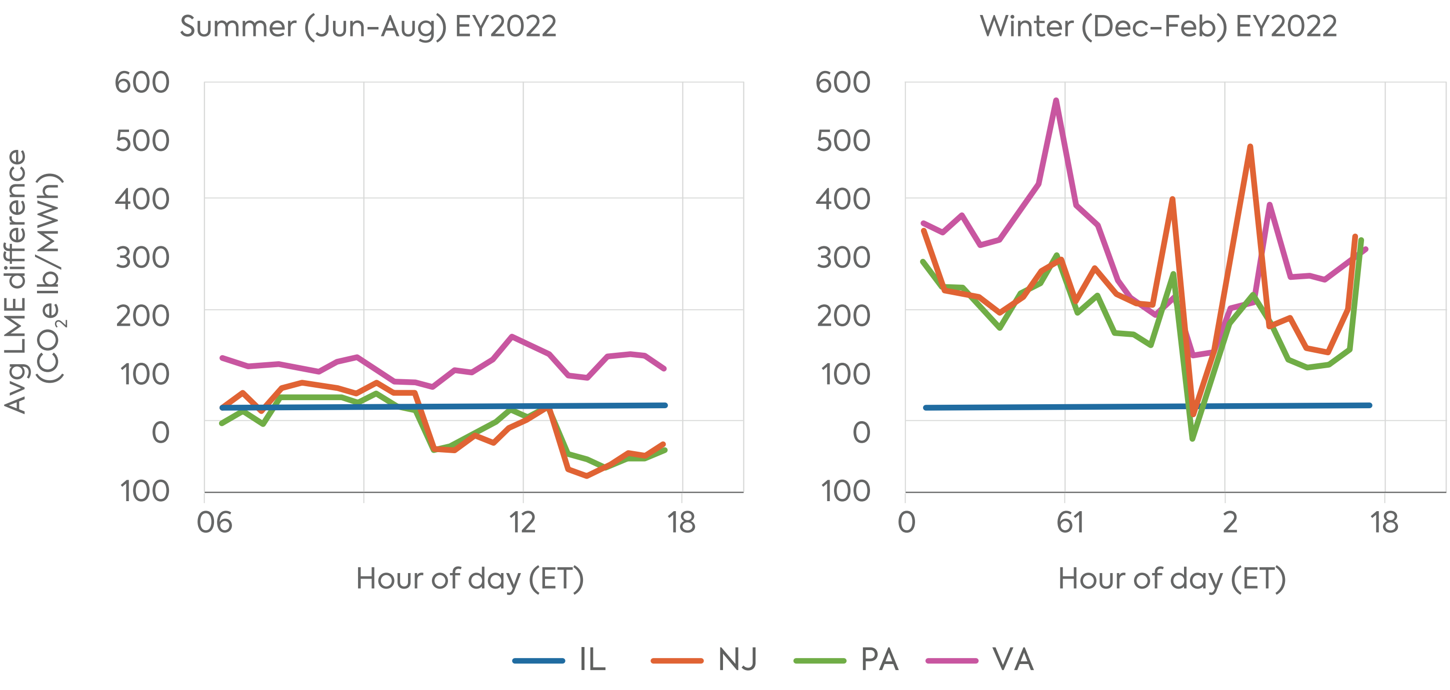


Note: A high LME will correspond to more emissions savings, as that means 1 megawatt-hour of renewable energy has a bigger impact to the grid at that place and time.

Average LMEs also differ across states, especially in winter. Illinois had the lowest average LMEs, but also had the largest spread in LMEs between summer and winter. This is attributable, at least in part, to the large amount of wind generation in Illinois, which typically produces more electricity in the winter months. Wind resources across the western PJM region, on average, produce 17% of their overall generation in summer and 45% in winter, with the remaining 38% produced in the spring/fall shoulder months. Average seasonal LMEs in Pennsylvania, Virginia, and New Jersey are less variable between seasons, likely because these areas rely more on thermal resources, which have a more constant GHG output. Intraday variability of generation also plays a major role affecting LMEs. Wind resources typically produce 3%–6% of their total generation per hour. Differences in which generation resource is the marginal unit (i.e., the last unit necessary to serve load in the area) as well as congestion lead the average LME to vary by an average of 200 pounds/megawatt-hour over the course of a day.

Figure 3 shows the difference in LMEs between Illinois, New Jersey, Pennsylvania, and Virginia over the course of a typical day. Hypothetical shifting of renewable generation from Illinois to either Virginia or Pennsylvania could reduce emissions in summer mornings or almost any time in winter, as these times and locations are associated with higher LMEs in those states.

Figure 3: Comparison of average New Jersey, Pennsylvania, and Virginia LMEs by hour to Illinois LMEs

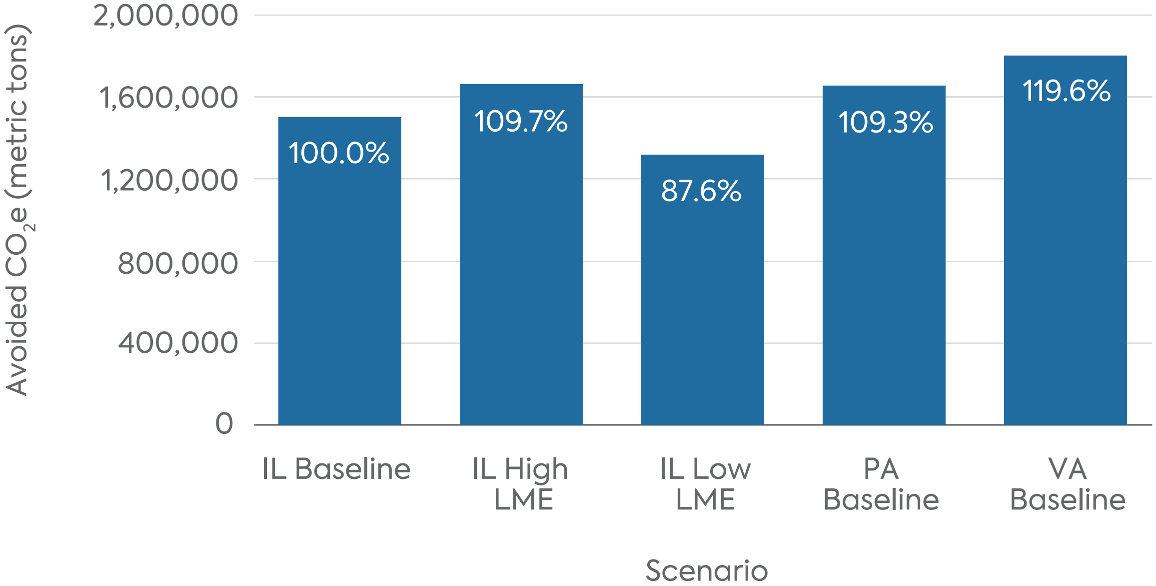


These seasonal and intraday changes in LMEs provide a potential opportunity for regulators to reward entities that "shift" their clean energy production from a time when and place where the grid is relatively clean to a time and place the grid is relatively dirty. This goal can be met by introducing carbon indexing into a state's RPS program by providing compliance entities a financial incentive to purchase and retire higher quality RECs. Physically, this energy shifting could be accomplished by deploying energy storage to "shift" production to times when the LMEs are higher. New generation resources would also receive a clear price signal to site in higher LME areas.[27]

The reduction in GHG emissions associated with shifting Class I REC production in time or location can be substantial, as shown in Figure 4. To quantify the GHG impacts, we shifted the 5 million megawatt-hours of Illinois wind production across the course of the day or shifted the location of the clean energy generation from Illinois to Virginia or Pennsylvania (per the five scenarios described in the methodology section).

- For the intraday shifting case, we first compared the Illinois Baseline case to the *Illinois High LME* scenario (i.e., REC production is shifted into the three dirtiest hours of the day) and the *Illinois Low LME* scenario (i.e., REC production is shifted into the three cleanest hours of the day) during the summer and winter seasons. Shifting production of clean energy into the cleanest hours resulted in approximately 12% more emissions (or, per the figure, less emissions savings) versus the baseline, while shifting production into the dirtiest hours resulted in approximately 10% less emissions.
- To calculate the benefits of geographic shifting, we compared the difference in GHG emissions intensity between generating RECs in Illinois versus generating RECs in either Pennsylvania or Virginia during the summer and winter periods. Moving the location of the clean energy production to Pennsylvania resulted in 9% less emissions, and moving it to Virginia resulted in approximately 20% less emissions.

Figure 4: Emissions savings under four study scenarios compared to the Illinois Baseline scenario



While shifting time and location together could potentially result in additive emissions reductions, this study did not examine such scenarios. Similarly, future work could examine how LMEs could shift emissions during the nonpeak shoulder months, as well as the degree to which longer-duration storage could be used for inter-seasonal shifting that could magnify potential emissions savings.

Discussion

The approach laid out in this paper can be implemented with relatively minor amendments to RPS program compliance regimes. Existing state RPS programs already track RPS compliance by utilities and competitive retail electricity providers. Implementing carbon indexing would require collection of three additional pieces of information: where a compliance REC was minted, when it was minted, and the LME of the grid at the location and time it was minted. LME and hourly REC-tracking efforts are more nascent outside of PJM, although some companies, such as RESurety and WattTime, offer LMEs across the country.

The effectiveness of carbon indexing RPS programs in terms of additional emissions reduction would likely hinge on at least three factors: how easy is it to shift generation, whether the economics work, and how LMEs may change over time.

First, effectiveness would depend on how successfully clean energy developers could shift intraday production from clean to dirty hours. Energy storage, the most likely time-shifting mechanism, can be expensive, and additional work would be necessary to determine the extent to which mass time-shifting is economically feasible. Another form of time-shifting would be using certain clean energy technologies that produce more of their power during the times of maximum emissions, such as substituting in solar generation, which tends to produce electricity during peak times, for wind production, which tends to produce electricity off-peak, though this is highly dependent on location-specific load profiles and the existing energy mix.[28]

Second, the impact of carbon indexing would depend on how successful additional pricing incentives were on shifting generation from lower emitting to higher emitting areas. Clean energy producers tend to locate in areas where development costs are lower, so any development premium for building in higher emissions localities would need to be exceeded by revenue gains from the program, all else equal. Further, as clean energy becomes increasingly dominant, curtailment of clean energy resources could occur (i.e., periods when clean energy production exceeds the ability of the grid to handle that power). Carbon indexing could allow a clean energy producer receiving extra carbon indexing revenue to reflect a higher willingness to pay to produce during a period of high curtailment risk. These clear price signals could then be incorporated into market dispatch decisions, allowing for more efficient allocation of curtailment responsibilities.

Third, LMEs are affected by the available energy mix as well as transmission constraints. As the US grid evolves, LMEs may continue to reflect marginal fossil fuel resources (typically natural gas) or may drop significantly if renewables are able to meet demand. However, transmission constraints can create submarkets in which LMEs are higher in the transmission-constrained area (or, conversely, artificially low in areas where clean energy is bottled up). Because LMEs reflect actual grid conditions, inclusive of transmission topology, they reflect the market as it actually exists. Changes to transmission infrastructure and changes in weather patterns would need to be considered carefully in estimating future LMEs and subsequent GHG savings.

Overall, the size of the addressable RPS compliance market is large and growing. For Energy Year 2022, New Jersey's load-serving entities were required to procure Class I RECs equal to 21% of total load served.[29] Current law requires that this percentage increase to 50% of New Jersey's load by 2030. Recent proposed legislation would increase the requirement to 100% by 2035.[30] Other states across the PJM footprint are also scheduled to expand their clean energy purchases over the next decade.[31] With increasing overall demand for RECs, even a 10% boost to avoided emissions from Class I RECs could have large impacts on GHG abatement. This suggests that carbon indexing of REC obligations could provide significantly larger total GHG tonnage savings than demonstrated in this report's proof of concept.

Conclusions

This study analyzed the potential uses of newly available LME data to determine the benefits of shifting clean energy production temporally (e.g., across hours of the day) and geographically (e.g., from Illinois to Pennsylvania and Virginia). States could use these findings to improve the impact of their RPS programs by providing additional compliance credit to RECs that result in higher levels of emissions reductions.

Shifting energy production of modeled RECs in this study from the three hours a day with the lowest LMEs to the three hours with the highest LMEs resulted in a 22% reduction in GHG emissions (12% less and 10% more than the baseline, respectively). Just shifting REC production from an average hour to one of the three hours with the highest LMEs resulted in an approximately 10% reduction in GHG emissions. A similar benefit occurred by changing the location. Shifting from geographic areas with a relatively clean mix of generation to areas with a dirtier mix resulted in approximately 9%–20% reduction in GHG emissions versus the business-as-usual case, depending on the location.[32]

While the maximum impact of incorporating LMEs into RPSs is hard to gauge with any accuracy, the type of market-based incentive framework demonstrated in this paper would likely improve the emissions impact of such programs over the emissions-blind REC compliance strategies that currently prevail in RPS programs. Establishing a competitive market structure based on emissions reduction would encourage compliance REC purchasers to preferentially select clean energy produced wherever and whenever the grid is dirtiest.

Twenty-nine states and the District of Columbia have RPS mandates, and broad implementation of emissions-adjusted RECs could amplify their abatement potential, especially if novel methodologies and policy frameworks are shared among policymakers. And as grids get cleaner and more RECs are available, the need for differentiation—to direct new investment that best reduces emissions—will get stronger.

Appendix

We used the following methodology to aggregate LMEs and estimate a time and location to each REC retired in the scope of the analysis. We adjusted certain parameters based on the scenarios described in the paper using these same mathematical equations.

1. $LME\_Adjusted_{z,h,s} = \sum_{i \varepsilon z, t \varepsilon h, s} (LME_{i,t} \times Load_{i,t} / (\sum_{i \varepsilon z, t \varepsilon h, s} Load_{i,t})$
   - where $LME_{i,t}$ is the LME for every node *i* and time *t*
   - and $Load_{i,t}$ is the Load for every node *i* and time *t*
   - and $t\ \varepsilon\ h$ where *h* is the hour of the day (0–23)
   - and $t\ \varepsilon\ s$ where s is a season such that $t\ \varepsilon$summer (Jun–Aug) or $t\ \varepsilon$winter (Dec–Feb)
   - and $i\ \varepsilon\ z$ where z is a state defined as all nodes served by one or more specific utility companies[33]
2. $Probability_s = (\sum_{t \varepsilon s} Wind_t) / (\sum_t Wind_t)$
   - where $Wind_t$ is the total wind generation for the western PJM region at time *t*
3. $Probability_{h,s} = (\sum_{t \varepsilon h, s} Wind_t) / (\sum_{t \varepsilon s} Wind_t)$
4. $GHG\_Savings_{z,h,s} = REC_z \times Probability_s \times Probability_{s,h} \times LME\_Adjusted_{z,h,s}$
   - where REC_z is the total quantity of retired RECs originating from state *z*
5. $Total_z = (\sum_{h,s} GHG\_Savings_{z,h,s})$

The method can be mimicked at any granularity; though, for our analysis, we look at one originating state (|z| = 1) over a 24-hour daily cycle (|h| = 24) and across two seasons (|s| = 2).

Notes

1. PJM Interconnection, the operator of the largest electric grid in North America, provides LMEs on a nodal basis. Data is available at: https://dataminer2.pjm.com/feed/hourly_marginal_emissions/definition. Comparable data is also available from several third-party vendors, including REsurety (https://resurety.com/solutions/locational-marginal-emissions/) and WattTime (https://watttime.org/).

2. For ease of reading, we use RPS to refer to both types of programs. RPS and CES programs are administratively similar, and the methodology set forth in this paper would apply equally to both.

3. For a survey of state RPS programs, see Galen Barbose, "U.S. State Renewables Portfolio & Clean Electricity Standards: 2023 Status Update," Lawrence Berkeley National Laboratory, US Department of Energy, June 2023, https://eta-publications.lbl.gov/sites/default/files/lbnl_rps_ces_status_report_2023_edition.pdf.

4. M. Greenstone and I. Nath, "Do renewable portfolio standards deliver cost-effective carbon abatement?" Working paper 2019-62, Becker Friedman Institute for Economics, University of Chicago, November 2020, https://doi.org/10.2139/ssrn.3374942.

5. The preceding source (Greenstone 2020) says, "The estimates for the cost per ton abated range from $58 to $298, and are over $100 per ton in the majority of [the scenarios studied]."

6. For a general background on how LMEs can improve carbon accounting, see M. Lott et al., "Revising the Greenhouse Gas Protocol: Insights from an Expert Stakeholder Engagement," Center on Global Energy Policy, Columbia University, Dec. 4, 2023, https://www.energypolicy.columbia.edu/publications/revising-the-greenhouse-gas-protocol-insights-from-an-expert-stakeholder-engagement/.

7. See, Qingyu Xu and Jesse D. Jenkins, "Electricity System and Market Impacts of Time-based Attribute Trading and 24/7 Carbon-free Electricity Procurement," Zero Lab, Princeton University, Sept. 15, 2022, https://zenodo.org/records/7082212/files/Time-based%20Energy%20Attributes%20Report%20-%202022-09-15.pdf?download=1.

8. EPA definition: https://www.epa.gov/green-power-markets/renewable-energy-certificates-recs.

9. See, e.g., PJM EIS, "How do I sell RECs?" https://www.pjm-eis.com/getting-started/how-do-I-sell-recs.

10. See, e.g., Erik Paul Johnson, "The cost of carbon dioxide abatement from state renewable

portfolio standards," *Resource and Energy Economics* 36, no. 2, (May 2014), https://doi.org/10.1016/j.reseneeco.2014.01.001; see also Galen Barbose, "U.S. State Renewables Portfolio & Clean Electricity Standards: 2023 Status Update," Lawrence Berkeley National Laboratory, US Department of Energy, June 2023, https://eta-publications.lbl.gov/sites/default/files/lbnl_rps_ces_status_report_2023_edition.pdf.

11. Yuri Horwitz, "Reimagining REC Markets: Integrating Additionality and Emissionality into a New Carbon-Free Paradigm," SolSystems blog, Nov. 3, 2022, https://www.solsystems.com/reimagining-rec-markets/.

12. R. Feldman and A. Levinson, "Renewable Portfolio Standards," *The Energy Journal* 2023 44, no. 5 (Sept. 1, 2023): 1–20, https://journals.sagepub.com/doi/epdf/10.5547/01956574.44.4.rfel.

13. S&P Platts, "Platts to launch additional emissions-adjusted North American REC prices," Dec. 8, 2023, https://www.spglobal.com/commodityinsights/en/our-methodology/subscriber-notes/120823-platts-to-launch-additional-emissions-adjusted-north-american-rec-prices.

14. See, e.g., I. Riepin and T. Brown, "System-level impacts of 24/7 carbon-free electricity procurement in Europe," TU Berlin, Oct. 11, 2022, https://zenodo.org/records/7180098.

15. PJM zone map: https://www.pjm.com/library/~/media/about-pjm/pjm-zones.ashx.

16. New Jersey Board of Public Utilities, "2022 Progress Report on New Jersey's Resource Adequacy Alternatives," March 2023, https://www.nj.gov/bpu/pdf/publicnotice/Staff's%202022%20Resource%20Adequacy%20Investigation%20Report_2023%20Revisions.pdf.

17. PJM press release, "Marginal Emission Rates Added to Data Miner Tool," Sept. 10, 2021, https://insidelines.pjm.com/marginal-emission-rates-added-to-data-miner-tool/.

18. PJM press release, "PJM EIS To Produce Energy Certificates Hourly," Feb. 13, 2023, https://insidelines.pjm.com/pjm-eis-to-produce-energy-certificates-hourly/.

19. New Jersey energy policies also require the retirement of a number of non-Class I certificates, largely focusing on solar projects connected or deemed connected to New Jersey's distribution system. These include Solar Renewable Energy Certificates, Transition Renewable Energy Certificates, and Solar Renewable Energy Certificates-II. Additionally, New Jersey provides specific certificate policies for offshore wind and nuclear.

20. PJM API portal: https://apiportal.pjm.com/.

21. For wind profiles, see PJM, "Wind Generation," https://dataminer2.pjm.com/feed/wind_gen/definition.

22. Nodal LME are available at PJM, "Hourly Marginal Emission Rates," https://dataminer2.pjm.com/feed/hourly_marginal_emissions/definition.

23. PJM, "Hourly Load: Metered," https://dataminer2.pjm.com/feed/hrl_load_metered/definition.

24. PJM, "Data Miner 2 Guide for Historic Data Retrieval," 2019, https://www.pjm.com/-/media/etools/data-miner-2/data-miner-2-historic-data-guide.ashx.

25. For background information on REsurety's LME data, see https://resurety.com/solutions/locational-marginal-emissions/.

26. See PJM's new services queue, which tracks new requests for interconnection by location and generator technology: https://www.pjm.com/planning/service-requests/services-request-status.

27. Some observers have suggested that short-run locational marginal emissions may not provide a sufficient financial incentive to drive investment decisions. Developers, however, routinely use short-run energy market price signals to drive investments, and economic theory would suggest that developers will make investment decisions if the additional revenues outweigh the increased costs associated with locating in a more expensive area.

28. Offshore wind production also tends to have a flatter production profile, which could also shift production to more favorable hours.

29. New Jersey Assembly, A3723, 218th Legislature (March 22, 2018), https://pub.njleg.gov/bills/2018/A4000/3723_I1.HTM.

30. New Jersey Clean Energy Act of 2024, S237, (March 14, 2024), https://www.njleg.state.nj.us/bill-search/2024/S237/bill-text?f=S0500&n=237_U1.

31. Lawrence Berkeley National Laboratory, US Department of Energy, "Renewables Portfolio Standards Resources," https://emp.lbl.gov/projects/renewables-portfolio.

32. Emissions would not directly be affected, as REC retirement happens *ex post facto*, but theoretical annual emissions could shift over time as more generation may occur during those hours.

33. Defined as AECO, JPCL, PSEG, and RECO for NJ; METED, PECO, PPL, and PENELEC for PA; DOM for VA; COMED for IL. See PJM zone map: https://www.pjm.com/library/~/media/about-pjm/pjm-zones.ashx.

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