The Electricity Journal 37 (2024) 107383

Contents lists available at ScienceDirect

The Electricity Journal

journal homepage: www.elsevier.com/locate/tej

Cost and emissions impact of voluntary clean energy procurement strategies

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ARTICLE INFO

Keywords:
Carbon-free electricity procurement
Marginal emission rate
Decarbonization
100 % renewable electricity
Corporate strategy

ABSTRACT

Large electricity consumers, particularly companies in the technology sector, are pursuing several different strategies to reduce their Scope 2 emissions through clean energy procurement. We calculate the cost and effectiveness of four different clean energy procurement strategies: U.S.-wide annual energy matching, local annual energy matching, hourly energy matching, and carbon matching. Carbon matching requires balancing emissions attributable to electricity load with avoided emissions from clean energy procurement (calculated with locational marginal emission rates), while energy matching requires balancing load and clean energy generation on an annual or hourly timescale. We evaluated these strategies as pursued by large electricity consumers with two different load profiles located in five different U.S. regions which vary in regulatory structure. We find that carbon matching is the most cost-effective procurement strategy, with a cost between \$4.7 and \$7.6/MWh, and has the lowest carbon emissions abatement cost at \$13/t CO_2 displaced. We find that annual energy matching costs range from \$10/MWh to \$32/MWh, and that it does not guarantee carbon neutrality. Hourly energy matching costs are higher, ranging from \$68/MWh to \$181/MWh, depending on region and load profile, and it is the least cost-effective strategy at carbon emissions reduction, with abatement costs ranging from \$77/t CO_2 to \$161/t CO_2. These results suggest that targeting clean energy investment in regions where current renewable energy penetration is low and marginal emissions rates are high is the most effective way for individual actors to reduce Scope 2 carbon emissions and reach carbon neutrality.

1. Introduction

Over the past decade, large corporations have played an increasingly important role in the financing and development of clean energy projects by committing to long-term fixed price contracts (termed power purchase agreements, or PPAs) for the energy produced by the project. By 2020, corporate procurement represented 12 % of all solar and wind investment in the U.S. (Miller, 2020).

Corporate interest in clean (non-carbon emitting) energy procurement has been driven in large part by increased attention to Scope 2 carbon emissions, indirect carbon emissions associated with the use of energy produced elsewhere, such as the purchase of electricity from the grid. However, directly calculating Scope 2 emissions is not straightforward, due to unresolved methodological questions and lack of data availability. As a result, most corporations have focused on achieving “100 % renewable energy” goals, meaning that they procure an amount of renewable energy that matches or exceeds their electricity consumption on an annual basis, a strategy this paper refers to as “annual energy matching.” This method of mitigating Scope 2 emissions was sanctioned by the World Resources Institute in their 2015 Scope 2 Guidance amendment to the GHG Protocol Corporate Accounting and Reporting Standard (Sotos, 2015). The popularity of this strategy is evidenced by the RE100 initiative, a corporate renewable energy initiative with more than 400 members, all of whom are committed to reaching a 100 % renewable energy goal (RE100 Climate Group, 2022).

More recently, some corporations have expressed commitments that go beyond annual energy matching. For example, in 2018, Google announced that reaching 100% renewable energy was “just the beginning,” and that it was pursuing “sourcing carbon-free energy for [its] operations on a 24×7 basis” (Google, 2018). This goal, which we referr to in this paper as "hourly energy matching,” requires matching electricity consumption in each hour with contracted clean energy generated within the same balancing authority area, meaning a geographic area in which a single regional grid operator or balancing authority is responsible for balancing supply and demand. Microsoft has also announced the use of hourly energy matching as part of its 100/100/0

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https://doi.org/10.1016/j.tej.2024.107383
Received 21 June 2023; Received in revised form 19 November 2023; Accepted 21 February 2024
Available online 18 March 2024
1040-6190/

zero-carbon energy commitment (Joppa and Walsh, 2021).

While both annual energy matching and hourly energy matching focus on procuring a defined amount of energy, other corporations have sought to more directly account for their Scope 2 emissions by using procurement strategies that focus on carbon emissions rather than energy consumption. For example, the Emissions First corporate partnership supports the use of electricity grid emission rates, particularly marginal emission rates, as the basis for carbon footprint accounting and decision-making on clean energy procurement and load management (Emissions First, 2022).

Given the increasingly important role that corporate procurement is playing in the development of clean energy projects, it is critical that the procurement strategies adopted by the corporate community lead to the development of projects that will have the largest carbon emissions impact. An analysis of the costs and impacts of these different clean energy procurement strategies will help to focus corporate resources where they will be most effective at reducing electricity sector carbon emissions.

Some previous analyses have compared annual and hourly energy matching strategies for corporate clean energy procurement. Xu et al. (2021) evaluated the system-level impacts of 10 % of commercial and industrial load pursuing hourly energy matching in the PJM Interconnection (PJM) and California. Pepper et al. (2022) evaluated the cost of pursuing hourly energy matching for a community choice aggregator in California. Olson et al. (2023) evaluated the cost of annual energy matching and hourly energy matching for green hydrogen production in four grid regions run by Independent System Operators (ISOs) or Regional Transmission Organizations (RTOs): the Midcontinent Independent System Operator (MISO), the Southwest Power Pool (SPP), the Electric Reliability Council of Texas (ERCOT), and PJM. These analyses are limited in scope: Xu et al. (2021) and Pepper et al. (2022) only look at California and PJM. While these are large organized markets, they represent only a fraction of nationwide electricity customers, and their results are not necessarily applicable to regions with different sizes, regulatory structures, and geography. Olsen et al. (2023) look at more regions but still only choose large, ISO/RTO regions, and conclusions from their analysis of hourly energy matching are undermined by overly simplifying assumptions.

Other analyses have compared energy matching procurement strategies with emissions-focused strategies. Oates and Spees (2022) compared energy matching with an emission-focused procurement approach in ERCOT, finding that the emission-focused approach is the most cost-effective at displacing carbon emissions. He et al. (2021) compared the cost and carbon footprint of annual energy matching, hourly energy matching, and carbon matching in four ISO/RTO regions: PJM, MISO, the California Independent System Operator (CAISO), and the New York Independent System Operator (NYISO) using forecasted marginal emission rates to calculate carbon footprint. Again, both these analyses focus only on ISO/RTO regions, and their treatment of hourly energy matching is limited by simplifying assumptions.

This paper provides a novel analysis of corporate clean energy procurement strategies, with two main improvements over previous studies. First, we include five different balancing authority areas in the scope of the analysis, incorporating three non-ISO/RTO regions that (while they vary in size) are all smaller than typical ISO/RTO regions. This is important because it can be more difficult or costly to procure clean energy in non-ISO/RTO regions, and because smaller regions have less climatic diversity and thus more time-correlated wind and solar energy generation, making hourly energy matching more difficult to achieve. Second, we provide a full-fledged implementation of hourly energy matching, with least-cost procurement optimization including clean energy and battery procurement and siting battery operation, as well as the ability to target different carbon-free energy (CFE) scores, which represent the degree to which hourly energy matching has been achieved.

2. Methodology and problem formulation

2.1. Definition of corporate procurement strategies

We modeled the effects of large corporate energy consumers ('customers') pursuing four different clean energy procurement strategies:

1. **U.S.-wide annual energy matching** (current industry standard): the customer must match its total annual load with generation from procured clean energy. Clean energy can be procured in the customer's local balancing authority area or from any of the following five ISO/RTO markets: CAISO, PJM, the MISO, ERCOT, and SPP.

   This strategy meets the RE100 requirements because all energy is procured within North America.
2. **Local annual energy matching**: the customer must match its total annual load with generation from procured clean energy resources located in the same balancing authority area as the customer's load.
3. **Hourly energy matching**: the customer must match its load on an hourly basis with generation from procured clean energy resources located in the same balancing authority area as the customer's load. In addition, the customer can procure battery storage to shift clean energy between hours.

   This strategy meets the 24/7 Carbon-Free Energy requirements.
4. **Carbon matching**: the customer must reach carbon neutrality. Carbon neutrality is achieved when avoided emissions (carbon emissions displaced by incremental clean energy procurement) equal or exceed load emissions (carbon emissions attributable to the customer's load) on an annual basis. Avoided emissions and load emissions are calculated using locational marginal emission rates (LMERs). Clean energy can be procured within the customer's local balancing authority area, or from any of the following five ISO/RTO regions: CAISO, PJM, MISO, ERCOT, or SPP.

2.2. Customer details

The four clean energy procurement strategies were evaluated for customers located in five different balancing authority areas: CAISO, PJM, Duke Energy Carolinas (DUKE), Los Angeles Department of Water and Power (LADWP), Portland General Electric (PGE).

PJM and CAISO are ISO/RTO regions with multiple member utilities, tens of millions of customers, a large geographical spread, and which operate organized wholesale electricity markets. These regions have internal transmission constraints that can cause geographical spread in marginal prices and emissions rates. They also have differences which make them relevant for comparative analysis: PJM is a larger, regional (multi-state), system with low wind and solar energy penetration, while CAISO is a smaller, single-state system with high solar energy penetration. Resource availability is also a factor: CAISO has significant geothermal energy potential, while PJM does not.

DUKE, LADWP, and PGE are smaller regions served by vertically integrated electric utilities (VIEUs) that do not operate wholesale markets. This means that clean energy procurement can be more expensive and/or difficult. These three regions were chosen for their variation in customer base, geographical size, regulatory structure, and climate. Results from these regions can provide insights about a wide variety of similar VIEU regions.

For each of the five balancing authority areas, two customers were considered: one with a flat load profile, meant to represent data center, industrial, or hydrogen production load, and one with a commercial retail load profile, meant to represent a large retail store. Load profiles were assumed to be fixed, with no level of demand flexibility.

For the flat load profile, customer load was assumed to be 1 Megawatt (MW) in each hour, regardless of customer balancing authority area. The primary results in this paper are reported for customers with flat load. The commercial load profiles were sourced from the National Renewable Energy Laboratory's (NREL) End-Use Load Profiles for the U.

S. Building Stock database (Wilson et al., 2021).

2.3. Procurement cost and availability

Customers pursuing the U.S.-wide annual energy matching and carbon matching strategies could procure clean energy from up to six regions – five ISO/RTO regions with active PPA markets (CAISO, ERCOT, MISO, PJM, and SPP), and the customer's local balancing authority area. For the local annual energy matching and hourly matching strategies, customers were limited to procurement within the same balancing authority area as their load.

Clean energy procurement was available on a zonal level, and in ISO/RTO regions, procurement costs were calculated using zonal locational marginal prices (LMPs). Each zone had a specific wind and solar generation profile based on 2012 weather patterns, produced with NREL's PVWatts and Wind Toolkit tools (NREL, 2017 and Draxl et al. 2015).

For each specific clean energy or battery storage unit available for procurement, the procurement cost was calculated on 'net' basis as the generation-weighted difference between the 'contract price' and the 'value of energy' (see equation 1). The contract price (the cost to procure clean energy) was calculated using PPA index prices, or levelized cost of energy (LCOE) values where PPA prices were not available. The value of energy (revenue from the sale of energy) was calculated using LMPs in ISO/RTO regions and avoided cost rates (rates guaranteed to certain power producers by the Public Utility Regulatory Policies Act) in VIEU regions. We assume that the customer retires any clean energy attributes obtained, so no revenue is gained from their sale.

Net Procurement Cost Equation (1)

$$Procurement \quad Cost \quad \left(\frac{\$}{MW} - year\right) = \sum_{hour=1}^{8760} (Contract \quad Price_{hour} - Value \quad Of \quad Energy_{hour}) * Unit \quad Generation_{hour}$$

For ISO/RTO regions, the contract price was based on LevelTen Energy's 2022Q3 PPA Index Price (LevelTen Energy, 2022), and the value of energy was based on forecasted 2025 zonal hourly LMPs from TCR's long-term forecast of U.S. power prices.

For VIEU regions and for geothermal energy in CAISO, the contract price was set as the 'high' LCOE estimate from Lazard's LCOE Analysis v15.0, adjusted using U.S. Energy Information Administration (EIA) Electricity Market Module (EMM) regional multipliers and for inflation (Lazard, October 2021; U.S. Energy Information Administration, 2022). In these regions, the VIEU's avoided cost rate was used for the value of energy because these rates are guaranteed to certain qualifying facilities.

Utility-scale solar and wind energy were available in each balancing authority area except DUKE, where only utility-scale solar was available. Due to geographic limitations, wind and solar procurement in LADWP and wind procurement in PGE were only available through wheeling from CAISO (for LADWP) and Bonneville Power Administration (for PGE). This was accompanied by a firm transmission contract, which increased procurement costs. In CAISO, geothermal energy was also available for procurement. In DUKE and LADWP, rooftop solar PV was available for procurement due to the existence of specific avoided cost rates or tariffs for rooftop solar. However, due to its higher cost and lower capacity factor than utility-scale solar, it was not selected for procurement by any customer.

For the hourly energy matching strategy, battery energy storage (BES) in the same balancing authority area as the customer's load was available for procurement. BES construction and financing costs were drawn from Lazard's LCOS Analysis v7.0 and amortized into an Equivalent Annual Cost (EAC) for use in this single-year analysis.

Table 1 shows the clean energy and battery storage resources available for procurement in each balancing authority area, and the metrics used to calculate net procurement cost. This net procurement cost was multiplied on an hourly basis by generation to reach a value for cost (positive) or revenue (negative). For BES, hourly revenue and/or cost were calculated by multiplying charge or discharge by the zonal LMP.

Table 1
Net procurement cost calculation by balancing authority area and technology type.

Market type	*ISO/RTO*		*VIEU*		
Balancing authority area	**CAISO**	**PJM, ERCOT, MISO, SPP**	**PGE**	**DUKE**	**LADWP**
Utility-scale PV	PPA – LMP		LCOE * Regional multiplier – Avoided cost rate		
Utility-scale Wind			LCOE * Regional multiplier – Avoided cost rate (wheeled from BPAT)	-	LCOE * Regional multiplier – Avoided cost rate (wheeled from CAISO)
Geothermal	LCOE * Regional multiplier - LMP	-			
Utility-scale BES	Equivalent Annual Cost * Regional multiplier				

Within each balancing authority area, transmission constraints were not considered in terms of deliverability between clean energy generators and load locations. All energy produced by procured clean energy generators was eligible to be "matched" to load. However, the impact of transmission constraints is embedded in the zonal LMPs and MERs used to calculate cost and carbon footprint.

2.4. Strategy optimization and model formulation

In the procurement model, each customer pursued each strategy on a least-cost basis. For the annual energy matching strategies and the carbon matching strategy, the least-cost optimization was trivial – the customer simply procured the clean energy generator with the lowest procurement cost in \$/MWh (for the energy matching strategies) or lowest carbon abatement cost in \$/t CO_2 (for the carbon matching strategy).

The hourly energy matching strategy, however, has multiple features that make it non-trivial to optimize: 1) the customer must match energy in every hour, rather than annually; 2) the customer may choose to pursue a carbon-free energy (CFE) score lower than 100%, meaning it can choose to take grid energy in some hours; 3) the customer can procure battery storage and optimize its operation to help meet the hourly energy matching strategy and minimize costs. For this reason, the hourly energy matching strategy required a more detailed model formulation and the use of a commercial optimization solver (Gurobi).

For the hourly energy matching optimization model, the decision variables were the procured capacity of clean energy in each zone and for each generator type, the charge, discharge, and state of charge of the battery in each hour, the excess generation (positive difference between generation and load) in each hour, and the grid supply (negative difference between generation and load) in each hour (see Table 2).

The key constraints in the model formulation were the energy balance, the CFE target, and the excess energy limit. Decision variables are in boldface text.

Energy Balance (2): This constraint ensures that customer load in each hour is met by some combination of procured clean energy, battery operation, and supply from the grid.

Table 2
Decision variables used in the hourly energy matching model formulation.

Decision Variable	Description
$\boldsymbol{ProcuredEnergy_t}$	Total generation from procured clean energy resources
$\boldsymbol{Cap_{unit,area}}$	Procured capacity from generator 'unit' in zone 'area'[a]
$\boldsymbol{Ch^{es}_{t,area}}$	Battery charge MW in hour t in zone 'area'
$\boldsymbol{DC^{es}_{t,area}}$	Battery discharge MW in hour t in zone 'area'
$\boldsymbol{SOC^{es}_{t,area}}$	Battery state-of-charge in hour t in zone 'area'
$\boldsymbol{Excess_t}$	Excess generation above load in hour t
$\boldsymbol{GridSupply_t}$	Shortage of generation to match load in hour t

[a]In the model formulation 'Cap' was a decision variable representing procured capacity. 'ProcuredEnergy' is directly dependent on 'Cap' (it is 'Cap' multiplied by a normalized load profile), not a separate decision variable. It is shown here to simplify the equations.

$$\boldsymbol{ProcuredEnergy}_t + \sum_{area}\left(\boldsymbol{DC}^{es}_{t,area} - \boldsymbol{Ch}^{es}_{t,area}\right) - \boldsymbol{Excess}_t + \boldsymbol{GridSupply}_t - Load_t = 0\ \forall t$$

CFE Target (3): This constraint ensures that the input CFE target is met. The annual CFE score is calculated as the percentage of total hourly load that is matched by clean energy (including procured energy, energy shifted using battery storage, and clean energy from the grid). If the CFE target is 100%, then grid supply can only be used when the grid CFE score is 100%.

$$\frac{\sum_t \boldsymbol{ProcuredEnergy}_t + \sum_{area}(\boldsymbol{DC}^{es}_{t,area} - \boldsymbol{Ch}^{es}_{t,area}) - \boldsymbol{Excess}_t + (\boldsymbol{GridSupply}_t)(GridCFEScore)}{\sum_t (Load_t)} \geq TargetCFE$$

Energy/Load Ratio (4): This constraint limits the total amount of procured clean energy relative to total customer load. A lower energy/load ratio constrains "over-procurement" of clean energy and requires the customer to procure more battery storage to shift clean energy between hours.

$$\frac{\sum_t \boldsymbol{ProcuredEnergy}_t}{\sum_t Load_t} \leq EnergyLoadRatio$$

Battery storage was also subject to typical operating constraints not shown as equations here, including limits on hourly charging and discharging based on capacity, and a limit on total state-of-charge based on total storage. State-of-charge was tracked hour by hour for each battery procured. In addition, in each hour all batteries combined could only charge up to the amount of procured clean energy generation, though the battery storage and clean energy resources are not assumed to be co-located.

Objective Function (5):

The objective function for each strategy was to minimize cost, including procurement cost and battery operation:

$$minimize \quad \sum_{unit,area} \boldsymbol{Cap}_{unit,area} ProcurementCost_{unit,area} + \sum_{t,area} (\boldsymbol{Ch}^{es}_{t,area} - \boldsymbol{DC}^{es}_{t,area}) LMP^{es}_{t,area}$$

2.5. *Carbon emissions accounting and locational marginal emission rates (LMERs)*

Carbon emissions attributable to load and carbon displacement attributable to generation from procured clean energy resources were calculated using locational marginal emission rates (LMERs) from TCR's long-term market forecast. An LMER represents the change in system-wide grid emissions in response to a marginal increase or decrease in demand at a specific location and time. For a detailed description of LMERs and their use to calculate carbon footprints, see He et al. (2021).

LMERs can be used to attribute carbon emissions and displacement to individual generation assets, transmission lines, and loads on the power grid (Rudkevich et al. 2011, Tabors et al. 2021). As illustrated in Table 3, when LMER is applied to each asset in the system, the sum of each asset's LMER-based carbon footprint (net sum of carbon emissions and displacement) equals the total systemwide physical carbon emissions. This is not necessarily true for accounting schemes that use average emission rates.

Table 3 illustrates carbon emissions accounting for a simple balanced system using both direct physical accounting and LMER-based carbon footprint accounting. Column A shows the load or generation level of each asset in the network. For each generator, column B lists the physical carbon emissions rate and column C shows the total physical emissions (the product of generation level and physical emission rate). Column D shows the LMER at each location. In this simple example, the system is assumed to have no transmission constraints, and the gas turbine (GT) is the marginal generator. Therefore, all locations in the network observe the physical emission rate of the GT as their LMER. Column E shows the carbon footprint attributed to each asset.

The net carbon footprint of any collection of load and generation assets can be calculated by summing the individual assets' carbon footprints. For example, if Customer 1 procures 50% of the capacity of the wind generator, then its net carbon footprint would be 330,000 kg-CO_2 (480,000 kg attributed to load, and 150,000 kg avoided through wind generation). This framework incentivizes consuming electricity when and where LMERs are lowest and generating clean energy when and where LMERs are highest.

Real-time LMERs with temporal and spatial granularity are not widely available at present, but there is a broad movement to provide increased access to this data for carbon accounting and carbon-aware operating decisions. For example, the Infrastructure Investment and Jobs Act specifically calls for the U.S. Energy Information Administration (EIA) to collect and report hourly locational marginal greenhouse gas emission rates (H.R. 3684, 2021). The most reliable sources for producing nodal LMERs are balancing authorities because they have access to the most granular operating data and run the dispatch algorithms which identify marginal generators. PJM and ISONE have begun reporting LMERs, and other ISO/RTOs may follow.

3. Results

3.1. *Metrics used*

Three metrics were used to evaluate the clean energy procurement strategies.

Strategy cost ($/MWh) measures the required clean energy

Table 3
Sample carbon accounting using LMER for a simple, unconstrained network.

			Physical Emission		Marginal Carbon Footprint	
Type	**Asset**	**Generation or Load (MW)** [A]	**Physical Emission Rate (kg/ MWh)** [B]	**Physical Emissions (kg)** [C] = [A]×[B]	**Locational Marginal Emission Rate (kg/ MWh)** [D]	**LMER-based Carbon Footprint (kg)** [E]=[A]×([B]-[D])
Generator	Wind	500	0	0	600	-300,000
Generator	Coal	2000	1000	2,000,000	600	800,000
Generator	NGCC	1000	400	400,000	600	-200,000
Generator	GT	300	600	180,000	600	0
Sub-total Generation		*3800*		*2,580,000*		*300,000*
Load	Customer 1	-800	0	0	600	480,000
Load	Customer 2	-2000	0	0	600	1,200,000
Load	Customer 3	-1000	0	0	600	600,000
Sub-total Load		*-3800*		*0*		*2,280,000*
System Grand Total		**0**		**2,580,000**		**2,580,000**

procurement cost to achieve the goal of each strategy, divided by total load matched. For hourly energy matching, this cost also includes battery storage procurement cost and battery operation cost or revenue.

Net carbon footprint (metric tons CO_2, or t CO_2) measures the difference between carbon emissions attributable to electricity consumption ("load emissions") and carbon displaced by clean energy generation from incremental investment ("avoided emissions"), calculated using LMER. For hourly energy matching, net carbon footprint also includes the carbon emissions and displacement associated with battery operation. Note that net carbon footprint only considers emissions from electricity consumption and avoided emissions from investment in clean energy generation. It does not include emissions or offsets from any other source.

Carbon abatement cost (\$/metric tons CO_2, or t CO_2) measures the cost to achieve the goal of each strategy, divided by the amount of carbon displaced by each strategy. A lower value indicates the strategy is more efficient at displacing carbon. This metric does not consider the total carbon footprint of the customer, only the effectiveness of customer action.

3.2. Strategy cost

Fig. 1 compares the strategy cost of the four procurement strategies for a customer with the flat load profile.

Using the U.S.-wide annual energy matching strategy, customers in all balancing authority areas can procure the least-cost clean energy available, which is utility-scale PV in ERCOT at a net procurement cost of \$10/MWh.

The cost of the local annual energy matching strategy ranges from \$16/MWh in PJM to \$32/MWh in LADWP. Because this strategy restricts procurement to within the same balancing authority area as the customer's load, it will necessarily have a higher cost than the U.S.-wide annual energy matching strategy except when the customer's load is in the same balancing authority area as the lowest-cost procurement option (ERCOT). PJM and CAISO have a broad range of clean energy procurement options, but procurement costs are higher than in ERCOT due to lower resource quality (PJM) and market dynamics (CAISO). DUKE, PGE, and LADWP have limited procurement options, some of which involve additional cost due to the requirement of a firm transmission contract, resulting in higher prices than ERCOT.

The cost of the carbon matching strategy ranges from \$4.7/MWh in DUKE to \$7.6/MWh in LADWP. For this strategy, customers in all balancing authority areas can procure energy from the generator with the highest carbon displacement relative to procurement cost (this happens to be a utility-scale PV plant in southeast SPP). Thus, the difference in strategy cost across balancing authority areas is driven only by load carbon footprint, determined by the LMERs in each balancing authority area. Relative to the other balancing authority areas, DUKE has low forecasted LMERs, resulting in the smallest carbon footprint to displace and the lowest cost at \$4.7/MWh. On the other hand, LADWP has relatively high forecasted LMERs, resulting in a higher carbon footprint and the highest cost at \$7.6/MWh.

The cost of the hourly energy matching strategy greatly exceeds the costs of the other strategies. As shown in the discussion section, this cost reflects much higher procurement (MWh) of clean energy and the procurement and operating cost of battery storage to balance energy across hours. Hourly energy matching also exhibits the most variation in cost between the ISO/RTO regions and the VIEU regions – all VIEU regions have costs over \$150/MWh due to higher battery storage requirements and restricted clean energy procurement options, while CAISO and PJM have costs of \$68/MWh and \$93/MWh, respectively.

3.2.1. Commercial load profile – sensitivity analysis

So far, we have presented results for customers with flat load (i.e., the same demand in every hour of the year). For customers with commercial retail load, the results were broadly similar. Load profile is not relevant for the annual energy matching strategies because they only consider the sum of total load throughout the year. For hourly energy matching, load profile is important because load must be matched with clean energy in every hour, and the correlation between load and clean energy generation profiles can make a large difference in the amount of clean energy procurement and battery storage required.

Fig. 2a compares the strategy cost of hourly energy matching for customers with flat and commercial load profiles. In most regions, strategy cost is lower for customers with commercial load because that load profile tends to correlate better with solar PV generation than flat load. The exceptions are in CAISO, where geothermal energy is available for procurement (geothermal energy has constant generation, which matches better with flat load), and in PGE, where the load profile is skewed towards the early morning and late evening and the solar capacity factor is low.

Fig. 2b compares the strategy cost of carbon matching for customers with flat and commercial load profiles. While the results differ slightly because the carbon footprint of the customer's load is calculated using LMERs that vary on an hourly basis, the differences in strategy cost between the two load profiles are minimal, and carbon matching is the most cost-effective strategy for all customers regardless of load profile.

3.3. Carbon displacement and net carbon footprint

Fig. 3 shows avoided emissions as a percentage of load emissions for customers with a flat load profile pursuing each strategy. A value greater

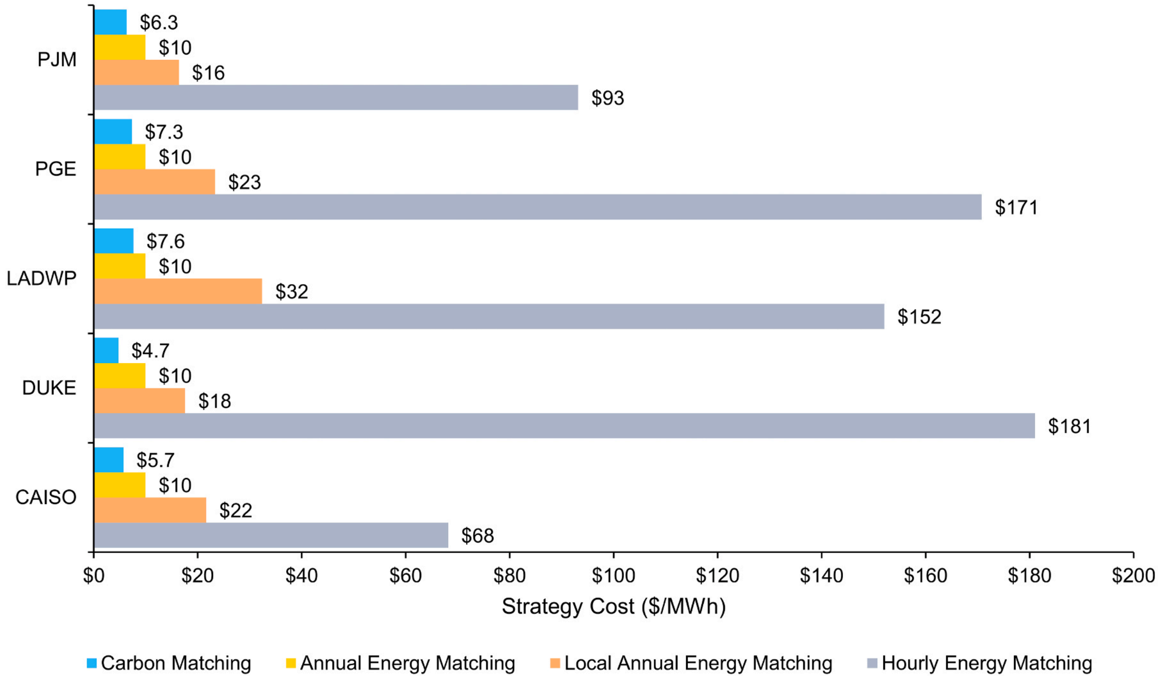

Fig. 1. Strategy cost. Comparison of strategy cost per MWh of customer load by strategy and customer balancing authority area for customers with flat load. For hourly energy matching, the target CFE score is 100 %.

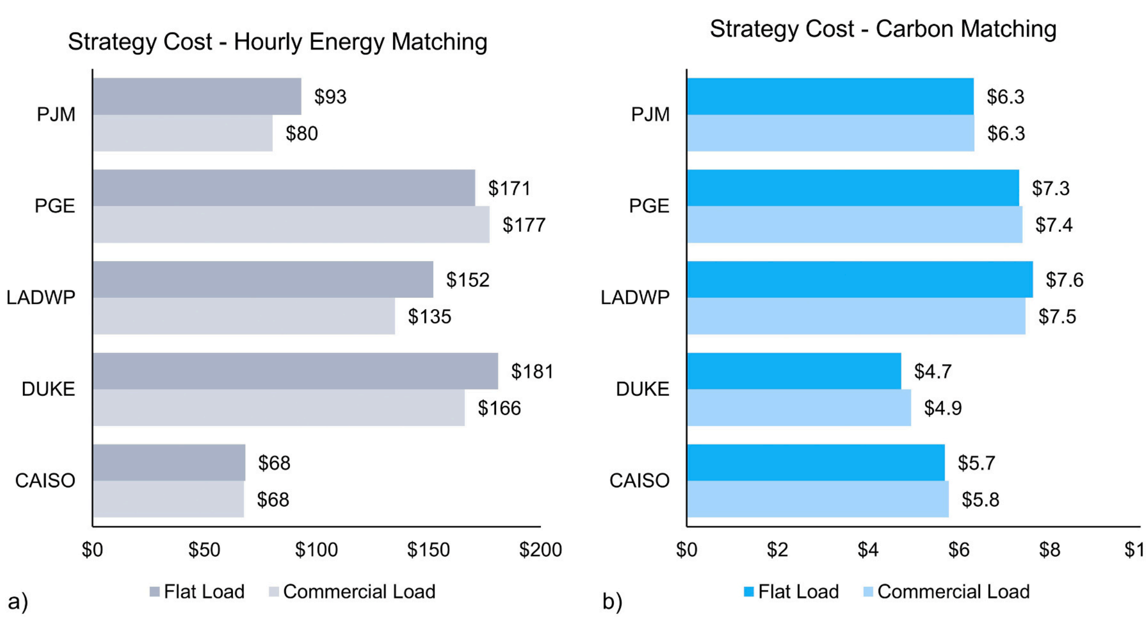

Fig. 2. Cost comparison by load profile. Strategy cost ($/MWh) comparison for the (a) hourly energy matching with 100% target CFE score and (b) carbon matching strategies for customers with commercial load and flat load in each balancing authority area.

than 100% represents a negative carbon footprint because avoided emissions displaced are greater than load emissions. Similarly, a value less than 100% represents a positive carbon footprint. Hourly energy matching results in a negative carbon footprint for all customers because hourly energy matching requires procurement of clean energy resources that generate significantly more than the customer's annual load. Carbon matching, by definition, results in a carbon footprint of zero (100% displacement) for all customers.

Neither the U.S.-wide nor the local annual energy matching strategy guarantees a negative carbon footprint because of differences in LMERs at the load and clean energy procurement locations. In CAISO, DUKE, and LADWP, the U.S.-wide annual energy matching strategy resulted in a lower net carbon footprint than the local annual energy matching strategy for both load profile types. For the customers with flat load, local annual energy matching achieves a negative carbon footprint in DUKE, PGE, and PJM. For customers with commercial load (not shown), local annual energy matching achieves a negative carbon footprint in PGE and PJM, but not in CAISO, DUKE, or LADWP.

3.4. Abatement cost

Fig. 4 shows the CO_2 abatement cost of each strategy for customers

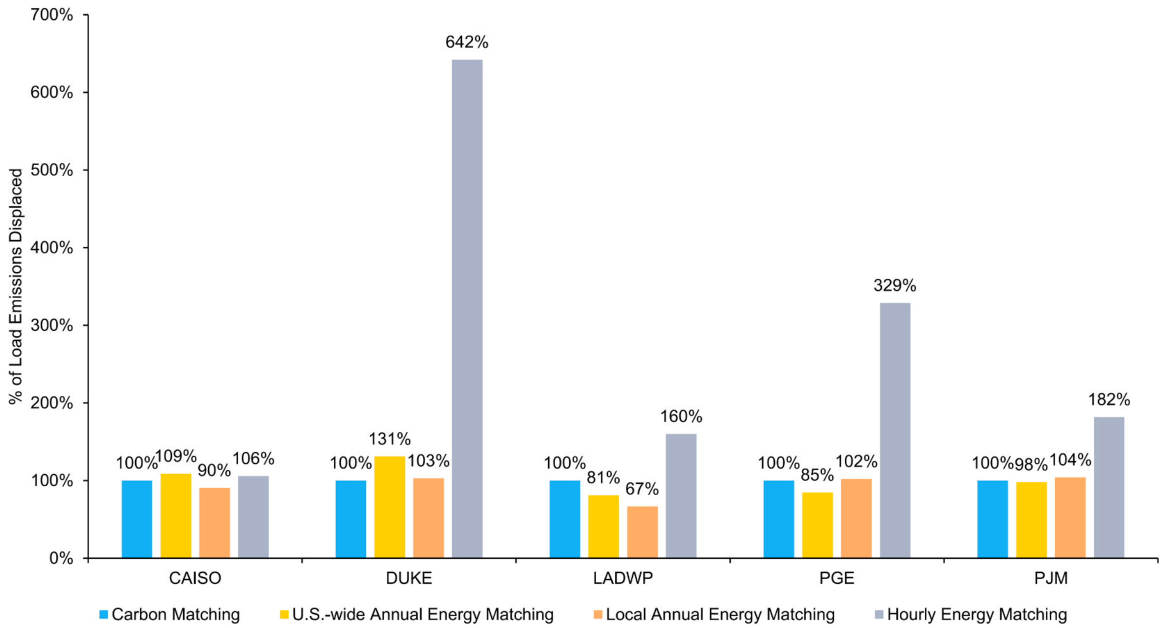

Fig. 3. Carbon Displacement. Carbon displacement as a percentage of load emissions for customers with flat load by customer location and strategy. A value of 100% represents carbon neutrality (zero net carbon footprint). Values greater than 100% represent a negative carbon footprint, and values less than 100% represent a positive carbon footprint.

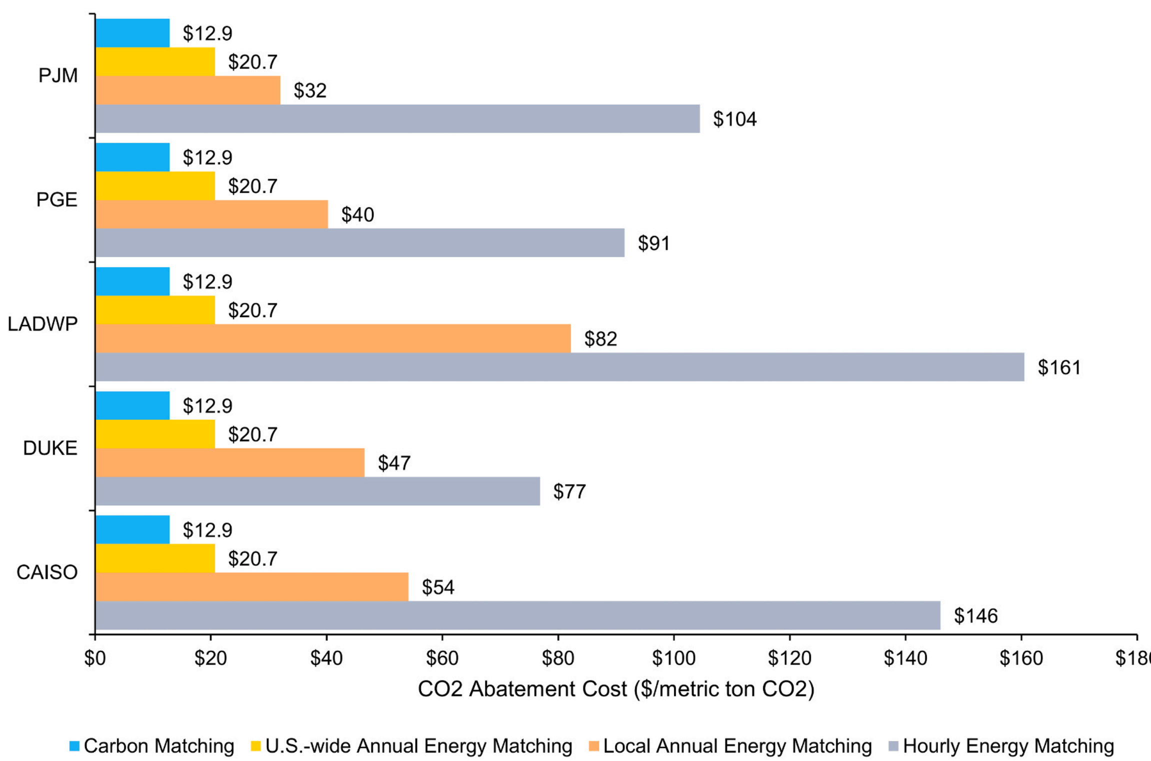

Fig. 4. Abatement Cost. CO_2 abatement cost by strategy for customers with a flat load profile in each balancing authority area. For hourly energy matching the target CFE score is 100%.

with a flat load profile.

Both the carbon matching strategy and the U.S.-wide annual energy matching strategy allow U.S.-wide procurement, meaning that the abatement cost of these strategies is the same for customers in all balancing authority areas.

Customers pursuing carbon matching procure energy in SPP because it has relatively low procurement costs and high LMERs, resulting in the lowest carbon abatement cost, at $12.9/t CO_2. U.S.-wide annual energy matching incentivizes customers to procure energy in ERCOT, where procurement costs are lowest, but because ERCOT has lower LMER than SPP on average, these investments are not as cost-effective in terms of displacing carbon emissions, with an abatement cost of $20.7/t CO_2.

The abatement cost of the local annual energy matching strategy ranges from $32/t CO_2 in PJM to $82/t CO_2 in LADWP. These higher

Table 4
Lowest CO_2 abatement cost (\$/t CO_2) for PV and wind in each balancing authority area.

Balancing Authority Area	PV	Wind
CAISO	\$54.1	\$83.1
DUKE	\$46.6	–
ERCOT	\$20.7	\$28.1
LADWP	\$82.2	\$123.4
MISO	\$29.0	\$31.7
PGE	\$40.2	\$112.9
PJM	\$48.3	\$31.0
SPP	\$12.9	\$17.9

abatement costs are driven by much higher procurement costs in the customer's local balancing authority area, especially the VIEU regions. The hourly energy matching strategy results in even higher abatement costs due to the need to procure battery storage, which has high procurement cost but little carbon abatement value, especially when optimized for least-cost operation. Note that while hourly energy matching results in a negative carbon footprint and high carbon displacement (see Fig. 3), it does so at a higher abatement cost than the other strategies.

4. Discussion

4.1. Carbon matching incentivizes efficient investment, while localizing energy matching decreases carbon abatement efficiency

The carbon matching strategy incentivizes customers to procure clean energy in regions with higher LMERs, because generation in those regions will displace more CO_2 per MWh generated. As a result, the carbon matching strategy requires less procurement overall (MWh) because of the positive difference in LMER between the load and generation locations. In this analysis, customers pursuing the carbon matching strategy procure PV in SPP, where PPA prices are relatively low and LMERs are relatively high, resulting in a low abatement cost.

Differences in the abatement cost of procured clean energy between balancing authority areas are significant and span an order of magnitude. Table 4 shows the PV and wind generators with the lowest abatement cost in each balancing authority area. SPP has several locations where both wind and PV procurement can displace carbon emissions at less than \$20/t CO_2. Prices in other ISO/RTOs range from \$20.7/t CO_2 for PV in ERCOT to \$83.1/tCO_2 for wind in CAISO. For VIEU regions, abatement costs are even higher due to the additional cost of wheeling contracts required to satisfy the "local" generation requirement. For all customers in this analysis, procuring PV in SPP results in a carbon abatement cost at least three times less than procuring energy in their local balancing authority area.

In this study, demand was considered fixed, with no level of flexibility. Traditional demand response, where a facility occasionally reduces load in response to high prices or a request from the system operator, would likely not materially impact the results because the cost of pursuing each strategy is not largely influenced by a single event or day of the year. However, a flexible demand program that allowed daily shifting of load between hours or locations could significantly reduce procurement costs for the carbon matching and hourly energy matching strategies, by shifting load to hours with lower LMERs (carbon matching) or higher wind and solar penetration (hourly energy matching).[1] This is an area for further work.

4.2. The cost of hourly energy matching varies by carbon-free energy score and location

The degree to which hourly energy matching has been achieved can be quantified using the CFE score, the percent of total load that has been matched with clean energy on an hourly basis (Google, 2021). As shown in the results section, hourly energy matching with a target CFE score of 100 % has the highest strategy cost and highest carbon abatement cost of all strategies studied. However, the strategy cost varies significantly with CFE score.

Fig. 5 shows the strategy cost of hourly energy matching for CFE scores of 95 %, 98 %, 99 %, 99.5 %, and 100 % (green bars). It also shows the strategy cost and CFE score of the local annual matching strategy (orange bar), which can be seen as a starting point for customers moving towards hourly energy matching. Results for customers with flat load are shown. These results show that most of the cost of hourly energy matching is incurred in matching the last 5 % of load. Stated differently, improving from a CFE score of 95–100 % more than doubles the cost of this strategy in all balancing authority areas.

Why does the last 5 % of hourly energy matching cost so much to achieve? Because of the intermittent nature of wind and solar generation, to ensure the generation matches load on an hourly basis customers must do the following:

1. Procure enough clean energy so that even in low output hours the customer still has sufficient generation to cover load. This naturally leads to excess generation during normal and high output hours which must be sold into the market, leaving the customer potentially exposed to price volatility.
2. Use battery storage to store clean energy when output is high and release it when output is low. This requires less energy procurement but increases costs due to battery storage procurement.

Additionally, the hourly energy matching results show wide variation in costs between balancing authority areas due to differences in procurement cost and clean energy availability. Balancing authority areas with large geographic footprints allow customers to procure energy from solar and wind generators with different generation profiles, which helps provide clean energy in a larger percentage of hours, reducing the need for battery storage.

As an example, Fig. 6 shows a ten-day period in PJM for a customer with a flat 1 MW load and 100% CFE score. In this scenario, the customer procured 10 MW of utility-scale PV, 2.6 MW of utility-scale wind, and 3.6 MW of 4-hour battery storage for a total cost of \$93/MWh to match its load in every hour.[2] The diversified portfolio of generation helps the customer cover more hours and reduces the need for battery storage. Despite that, the total clean energy procured was 2.5 times greater than the total customer load.

In contrast, in DUKE, where utility-scale wind procurement was not available, the flat load customer had to procure 36 MW of utility-scale PV and 7 MW of 4-hour battery storage for a total cost of \$181/MWh to match a 1 MW flat load with a 100 % CFE score. In this case, the total clean energy procured was 6.6 times greater than the total customer load.

4.3. Comparison to other studies

4.3.1. Hourly energy matching

Other studies have attempted to quantify the cost of hourly energy matching for commercial and industrial customers pursuing voluntary procurement (Xu et al. 2021) and for low-carbon hydrogen production

[1] With an annual energy matching strategy, only total load matters, so customers are not incentivized to shift load in ways that could lower their carbon footprint.

[2] Flat load was set to 1 MW for simplicity, but the results can be scaled linearly for larger load and procurement, which will likely be necessary for procurement of multiple resources to be feasible.

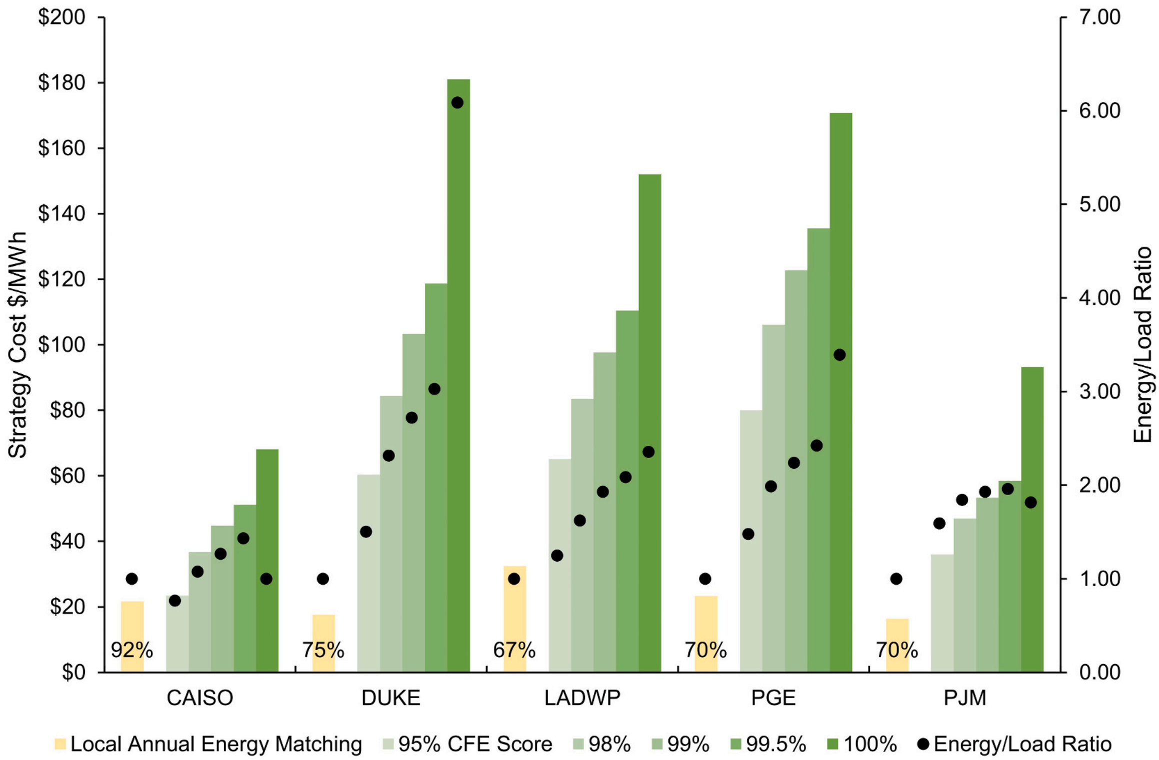

Fig. 5. Cost and energy/load ratio for hourly energy matching. Customer strategy cost ($/MWh) to achieve hourly energy matching at different target CFE scores (95 %, 98 %, 99 %, 99.5 %, and 100 %, shown with green bars). Strategy cost and CFE score of local annual energy matching is shown with the yellow bar and label, respectively. Black dots indicate energy/load ratio (right axis), equal to total procured energy divided by total load. This is for a customer with flat load and no limit on energy procurement.

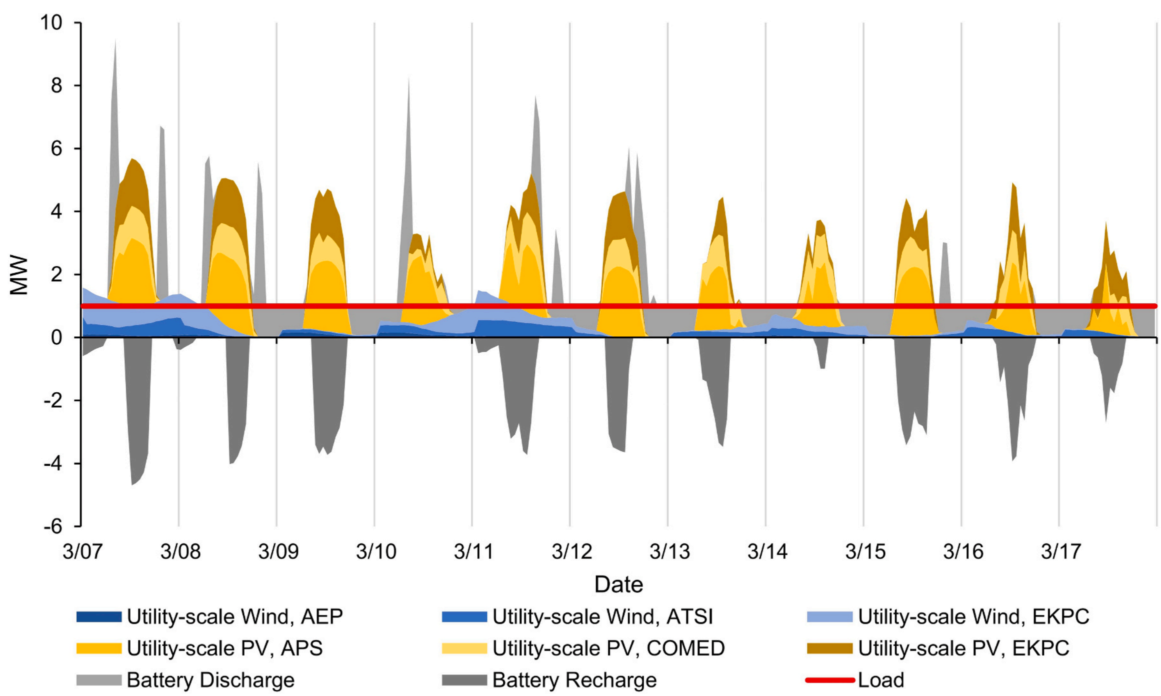

Fig. 6. Hourly generation for an hourly energy matching customer in PJM. Hourly generation and battery operation over a 10-day period in 2025 for a customer in PJM with flat load and targeting a 100 % CFE score. Acronyms indicate zone within PJM where generator is located (AEP: American Electric Power, APS: Allegheny Power, ATSI: American Transmission Service, COMED: Commonwealth Edison, EKPC: East Kentucky Power Cooperative).

(Olson et al., 2023), especially in the context of comparing hourly and annual energy matching.

Xu et al. 2021 found that hourly energy matching with a 100 % CFE score cost $79.7/MWh in California and $99.5/MWh in PJM using current technologies, comparable to our results of $68/MWh in CAISO and $93/MWh in PJM.

Olson et al. (2023) compares local annual and hourly energy matching for a hydrogen producer running at 90 % capacity factor (not running during the highest-priced 10 % of hours). In PJM, they found that hourly energy matching added a 19–61 % premium to local annual energy matching across scenarios, while we found a 55–56 % premium for hourly energy matching with a 90 % CFE score in PJM.

Direct comparisons show that our hourly energy matching costs are comparable to other studies for ISO/RTO regions; however, there are no relevant comparisons available for the cost of hourly energy matching in VIEU regions. We show that total cost in these regions is much higher than for ISO/RTO regions, suggesting that some hourly energy matching constraints (such as procurement location or CFE score) may need to be relaxed to pursue hourly energy matching in these regions in a cost-effective manner.

4.3.2. Carbon matching

Oates and Spees (2022) compared a carbon matching strategy against energy matching strategies to measure effectiveness of carbon abatement for procurement in ERCOT. They found carbon abatement costs of $19/ton for annual energy matching, $9/ton for LMER-based carbon matching, and $47/ton for on-site hourly energy matching. In comparison, we found abatement costs of $21/ton for annual energy matching, $13/ton for carbon matching, and between $104–146/ton for hourly energy matching in ISO/RTO regions. The hourly energy matching costs differ because Oates and Spees modeled the strategy as co-located generation matching only 60 % of energy consumption, rather than using grid-connected generation and a CFE score metric. Otherwise, the results are similar, and both show that carbon matching is the most effective strategy in terms of carbon abatement cost.

5. Conclusion

5.1. Takeaways

The results show that carbon matching has the lowest abatement cost and the lowest strategy cost, meaning it is the most cost-effective strategy to pursue for any customer. Moreover, carbon matching guarantees a net-zero carbon footprint. U.S.-wide annual energy matching was also cost-effective, but it does not guarantee carbon neutrality.

In this analysis, both the hourly energy matching and local annual energy matching strategies required procurement of energy within the same balancing authority area as load. The results show that localizing energy procurement typically increases costs and net carbon footprint, resulting in more money spent but fewer carbon emissions displaced. This is because forcing clean energy projects to be procured in the same balancing authority area as load prevents buyers from accessing the most economic and carbon-impactful projects.

In addition, while the carbon matching strategy incentivizes procuring energy in regions with high LMERs, the hourly energy matching strategy incentivizes procuring energy in regions that already have a large share of clean energy, because it requires less investment to reach a high CFE score. Thus, hourly energy matching incentivizes investment in clean energy in the balancing authority areas where it is least needed, and where it displaces relatively few carbon emissions.

5.2. Future work

An important aspect of the use of LMERs for carbon accounting is that they, like marginal prices, reflect the current power system on an hourly and nodal basis but do not capture long-term market and grid dynamics. For this reason, when making a clean energy investment guided by LMERs, potential buyers must consider future changes to grid mix, dispatch order, and hourly market dynamics, just like they would need to when making an investment based on future prices.

This study only assessed the costs and carbon benefits for a single year (2025). However, clean energy investments are made on a long-term basis, as PPAs often have 10- to 20-year terms. Future work could calculate long-term costs and avoided emissions for different strategies and identify upside and downside risks to investors.

When evaluating strategies, we assumed that customers had perfect foresight of load, LMERs, and procurement costs. In practice, there will be substantial uncertainty associated with these values, especially on an hourly basis. Future work could use probabilistic forecasts of wind and solar generation and load and different market scenarios, to assess the cost of reaching each goal (and, for hourly energy matching, different CFE scores) with different confidence levels.

Funding

This research was supported by a research grant from Meta Platforms, Inc.

CRediT authorship contribution statement

Alexander Derenchuk: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Hua He:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Richard Tabors:** Conceptualization, Funding acquisition, Resources, Supervision, Writing – review & editing. **Aleksandr Rudkevich:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

There is no other financial interested.

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