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Article

Behind-the-Meter Solar at Hyperscale Data-Center Campuses: A Resource-Graded Carbon-Price Threshold Across Eleven U.S. Markets

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Abstract: Grid interconnection and delivery capacity, rather than generation cost, have become the binding constraint on serving hyperscale electricity loads in many U.S. markets. We show that the carbon price required to bring on-site solar into a cost-optimal campus portfolio can be read directly from the local solar resource: across eleven U.S. data-center market archetypes the threshold falls from approximately \$230/ton at an annual solar capacity factor of 0.147 to \$110/ton at 0.238, a near-linear relationship (R^2=0.97) that gives developers a single-parameter screening rule for siting. The result comes from a reproducible framework built only from public data, coupling a levelized-cost and Monte Carlo screening layer to a temporally-resolved capacity-expansion and dispatch optimization that co-optimizes investment and hourly operation and prices battery storage explicitly, run on real hourly NREL PVWatts V8 profiles. Because dispatchable gas capacity is retained for firmness in every scenario, on-site solar competes against gas's variable cost rather than its full levelized cost; this is why the threshold is graded by resource and why it lies well above current U.S. carbon prices, with gas remaining least-cost firm supply in every market at carbon prices up to at least \$100/ton. The relationship survives more favorable PV assumptions and a temperature-responsive cooling load. All code, inputs, and outputs are openly archived.
Keywords: behind-the-meter power; data centers; levelized cost; energy storage; capacity-expansion optimization; carbon pricing; grid interconnection

1. INTRODUCTION

Data centers and artificial-intelligence (AI) workloads are pushing electricity demand up faster than power infrastructure can be planned and built. The International Energy Agency estimates global data-center electricity consumption at approximately 415 TWh in 2024 (about 1.5% of global electricity) and projects it to more than double, to roughly 945 TWh, by 2030 (IEA, 2025). These projections extend a longer measurement record. Early bottom-up accounting established the basis for tracking data-center electricity use (Koomey, 2008); subsequent recalibration showed that efficiency gains had, for a period, decoupled computation growth from energy growth (Masanet et al., 2020). The recent inflection has two causes: some of those efficiency gains are exhausted, and AI is energy-intensive. In the United States, a Department of Energy–publicized, Lawrence Berkeley National Laboratory–led assessment projects data-center load to double or triple by 2028 (DOE, 2024a). The grid-side consequences of this growth (consumption patterns, stability risks, market impacts) are the subject of a rapidly forming literature (Bu et al., 2026). Individual hyperscale campus loads of 100–300 MW are now common; some planned facilities exceed 1 GW. The carbon intensity of such a campus is set jointly by its supply choices and the grid mix at its location (Siddik et al., 2021), which is why the analysis here is location-explicit.

At the same time, interconnection processes and grid buildouts struggle to keep pace. The U.S. Department of Energy (DOE) Transmission Interconnection Roadmap reports that queue volumes have quadrupled since 2010 to approximately 2,600 GW, with time-to-interconnect more than doubling (DOE, 2024b). A peer-reviewed statistical analysis of U.S. interconnection queues confirms that most projects entering queues do not reach commercial operation and that connection timelines and costs have risen substantially (Gorman et al., 2024). The mismatch between load-growth timelines (typically 18–36 months from site selection to energization) and interconnection timelines (often 3–5 years or more) has made behind-the-meter (BTM) generation a practical necessity for meeting schedules.

Compounding this, transformer and substation supply chains have emerged as independent bottlenecks. Distribution-transformer lead times rose from roughly 3–6 months in 2019 to 12–30 months by 2023 (DOE, 2022); large-power-transformer lead times are reported at 80–210 weeks (NIAC, 2024) and up to 36–60 months (DOE, 2024c). These time constants rival or exceed generation-project schedules, making hardware availability a first-order determinant of feasibility.

What the literature lacks is a single reproducible framework that evaluates technology economics, grid-constraint severity, equipment bottlenecks, and carbon-policy exposure together, while respecting the hour-by-hour matching of supply and demand and the geographic variation of solar resource. This paper builds that framework: levelized-cost screening coupled to a temporally-resolved, storage-inclusive optimization, applied across eleven public U.S. data-center market archetypes using real hourly solar data and only public assumptions. The headline finding is that dispatchable gas remains the least-cost firm supply in every market at carbon prices up to at least \$100/ton, with on-site solar entering only above a resource-graded threshold of roughly \$110–230/ton.

The paper proceeds as follows. Section 2 reviews the literature; Section 3 states the hypotheses; Section 4 describes data, equations, and the optimization; Section 5 presents results; Section 6 discusses them; Section 7 draws implications; Section 8 concludes.

1. LITERATURE REVIEW

2.1. Interconnection Backlogs and the Transmission-Development Gap

Interconnection backlogs are widely documented (DOE, 2024b). A peer-reviewed analysis of tens of thousands of interconnection requests provides statistical treatment of queue attrition, completion rates, connection costs, and timelines, finding that most projects do not reach commercial operation and that completion times and network-upgrade costs have risen (Gorman et al., 2024). FERC Order 2023 introduced cluster-based study processes, but implementation varies and legacy backlogs persist. This literature documents the problem but rarely evaluates the economic consequences for individual campus developers deciding whether to deploy BTM alternatives.

2.2. Supply-Chain Bottlenecks in Grid Hardware

Transformer bottlenecks operate independently of interconnection reform. Distribution-transformer lead times rose to 12–30 months by 2023 (DOE, 2022); large-power-transformer lead times reach 36–60 months (DOE, 2024c) and 80–210 weeks (NIAC, 2024), with industry corroboration near 128–143 weeks in 2025 (Reuters, 2025). This literature is technical and does not connect equipment constraints to portfolio economics.

Table 1 summarizes transformer and substation lead-time evidence, which are critical-path constraints for both grid and BTM pathways.

Table 1. Transformer and substation lead-time evidence.

Constraint	Public lead-time evidence	Planning implication
Distribution transformers	~3–6 months (2019) → ~12–30 months (2023) (DOE, 2022)	Feeder upgrades can be schedule-bound
Large power transformers	~36-month lead times; up to ~60 months (DOE, 2024c)	Can exceed campus construction windows
Large transformers (NIAC)	~80–210 weeks (NIAC, 2024)	Hardware scarcity can dominate schedules

Constraint	Public lead-time evidence	Planning implication
Market corroboration	GSUs ~143 weeks; power transformers ~128 weeks, 2025 (Reuters, 2025)	Confirms ongoing severity

ERCOT reports an 18–30-month interconnection process for generation ≥10 MW (ERCOT, 2024), and other operators report multi-year timelines (DOE, 2024b; NYISO, 2023). The peer-reviewed queue analysis of Gorman et al. (2024) confirms statistically that completion is the exception and that timelines and network-upgrade costs have risen. For a campus requiring both new interconnection and large transformers, the critical path can extend to 4–6 years. Figure S1 in the Supplementary Materials renders these lead-time ranges against the typical 18–36-month campus construction window.

2.3. Technology Economics, the Value of Variable Renewables, and Storage

Generation and storage economics are well characterized in public planning sources (Cole and Karmakar, 2025; EIA, 2024a; Lazard, 2025; NREL, 2024). A peer-reviewed literature shows, however, that levelized cost alone misstates the value of variable renewables, because it ignores temporal matching. The market value of solar and wind declines with penetration (Hirth, 2013), and the reliability of solar- and wind-dominated supply is geophysically constrained: even large, optimally sited systems leave many hours of unmet demand without substantial storage or firm capacity (Tong et al., 2021). Storage reduces curtailment and emissions and enables deeper decarbonization, but its cost is first-order (Arbabzadeh et al., 2019), and the levelized cost of storage frequently exceeds the value of shifted energy unless resource and cost conditions are favorable (Comello and Reichelstein, 2019; Petrollese, 2025). Matching a continuous load with clean power around the clock, directly analogous to a 24/7 data-center load, carries a real premium that firm dispatchable clean resources reduce (Riepin and Brown, 2024). Carbon accounting is likewise temporally sensitive: annual-average emission factors bias results relative to hourly accounting (Miller et al., 2022). This literature implies that a portfolio model ignoring temporal matching and storage cost will systematically overstate solar; the optimization in Section 4.4 is designed around exactly that point.

2.4. Campus-Scale Procurement and the Analytical Gap

Work on data-center procurement has focused on renewable power-purchase agreements and sustainability commitments, with less attention to time-to-power and equipment availability. Recent reviews survey AI data-center energy demand and its grid impacts (Bu et al., 2026) and data centers' role in accelerating renewable-energy adoption (Ziaei et al., 2026), but they stop short of the campus-level supply-investment question. Closest to our setting, Rollinson et al. (2025) optimize off-grid wind–solar–battery–gas systems for five European hyperscale hubs; the grid-constrained U.S. campus problem (grid import as a portfolio component, carbon pricing, equipment lead times on the critical path) remains unaddressed. Open, reproducible capacity-expansion tooling for temporally-resolved investment-and-dispatch modeling now exists (Brown et al., 2018), lowering the barrier to firming-aware, multi-market analysis. No existing study integrates technology-level economics, interconnection-constraint data, equipment lead times, and carbon-pricing scenarios in a single reproducible framework that respects temporal matching and geographic resource variation at campus scale. That is what this study does.

3. HYPOTHESES

H1. Under grid-capacity constraints, the least-cost campus portfolio includes dispatchable gas generation unless emissions pricing materially penalizes combustion.

H2. Internalizing carbon prices shifts the cost-optimal portfolio toward on-site solar, but only above a high, resource-dependent threshold that scales with solar capacity factor. Below that threshold dispatchable gas remains least-cost, and where solar does enter it supplies a minority of energy, with gas retained as the firm-capacity backbone.

H3. In a counterfactual "relaxed grid" scenario, BTM power remains economically rational for a non-trivial set of conditions because it acts as a resilience resource and a schedule hedge, and becomes cost-rational on energy economics once grid prices exceed the full (fixed plus variable) cost of on-site generation.

H4. Transformer and substation lead times become binding constraints for both grid expansion and BTM deployment; time-to-power is jointly determined by interconnection processes and equipment supply chains.

H5. For hyperscale 100–300 MW campuses, non-power constraints (transformers, permits, labor, water, site readiness) can dominate the critical path even when generation-technology costs are favorable.

4. MATERIALS AND METHODS

The framework uses linked layers: a levelized-cost-of-energy and levelized-cost-of-storage (LCOE/LCOS) calculator, a Monte Carlo screening of gas-price uncertainty, and a temporally-resolved, storage-inclusive capacity-expansion and dispatch optimization run across eleven markets. All models are Python and openly archived (see Data Availability Statement); every data source is listed in the Supplementary Materials. Figure 1 summarizes how the layers connect.

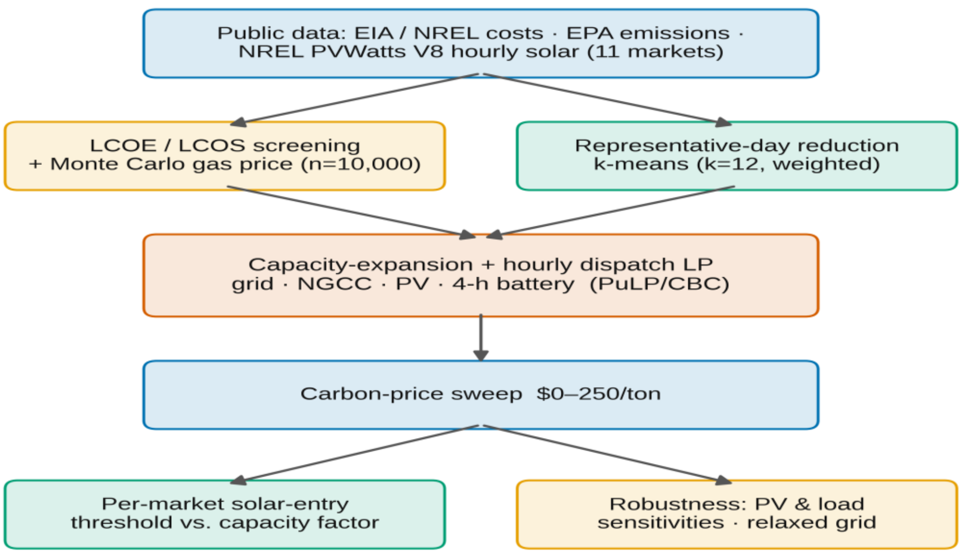

Figure 1. Framework workflow. Public cost, emissions, and hourly solar data feed a levelized-cost/Monte Carlo screening layer and a k-means representative-day reduction; both feed the capacity-expansion and hourly-dispatch linear program, which is swept over carbon prices of $0–250/ton to locate each market's solar-entry threshold and its robustness to PV and load sensitivities.

4.1. Data Sources

Technology cost and performance use the U.S. Energy Information Administration compendium (EIA, 2024a); battery cost uses National Renewable Energy Laboratory (NREL) projections (Cole and Karmakar, 2025) and the NREL Annual Technology Baseline (NREL, 2024); levelized-cost cross-checks use Lazard (2025). Combustion emissions use U.S. Environmental Protection Agency factors (EPA, 2025); financing uses the EIA Electricity Market Module (EIA, 2024b). Interconnection and lead-time evidence use government and industry reporting (DOE, 2022; DOE, 2024b; DOE, 2024c; NIAC, 2024; Reuters, 2025) and the peer-reviewed queue analysis of Gorman et al. (2024). Hourly solar-resource and ambient-temperature profiles were obtained from NREL PVWatts V8 (NSRDB PSM V3 typical-meteorological-year data) for eleven publicly recognized U.S. data-center market archetypes, using identical system settings across all sites (single-axis tracking; DC-to-AC ratio 1.2; 14% system losses; 180° azimuth) so that only the location, and therefore the climate, varies. Representative public metro coordinates were used; no specific facility location is identified. Exact request parameters are listed in Supplementary Materials, Section S4.

4.2. Model Inputs and Harmonization

Monetary values use the published basis (2023 USD). Financing uses the EIA baseline (approximately 6.7% discount rate) (EIA, 2024b), giving a capital-recovery factor of 0.0782 over a 30-year life and 0.108 over a 15-year battery life. Gas CO_2 conversion uses 53.06 kg CO_2/MMBtu (EPA, 2025). The headline campus scenario is a flat 200 MW load; a temperature-responsive load is examined as a sensitivity (Section 4.6). Grid energy is priced at a flat $35/MWh with a 100 MW import cap in the base case.

Table 2 compiles public inputs. The combustion-turbine row is reported for a single sourced configuration, and the storage parameters used by the optimization (a four-hour battery split into power and energy capital) are stated explicitly.

Table 2. Technology cost and performance inputs (2023 USD).

Technology	CAPEX	FOM ($/kW·yr)	VOM ($/MWh)	Heat rate (Btu/kWh)	Source
Gas CC (H-class, 627 MW)	$921/kW	15.51	3.33	6,226	(EIA, 2024a)
Gas CT (aeroderivative, 211 MW)	$1,606/kW	9.56	5.70	9,447	(EIA, 2024a)
Solar PV (single-axis, 150 MW)	$1,502/kW	20.23	0	n/a	(EIA, 2024a)
PV + 4-h storage (AC-coupled)	$2,175/kW	38.39	0	n/a	(EIA, 2024a)
Li-ion BESS, 4-h (model: power/energy split)	$150/kW power + $280/kWh energy	2.5% CAPEX	0	n/a	(Cole and Karmakar, 2025)
Onshore wind (200 MW)	$1,489/kW	33.06	0	n/a	(EIA, 2024a)
SMR (6×80 MW)	$8,936/kW	121.99	3.19	10,046	(EIA, 2024a)

Note. CC = combined cycle; CT = combustion turbine; BESS = battery energy storage system; SMR = small modular reactor. EIA values are 2023 USD. The optimization uses the power/energy-split BESS basis at a fixed four-hour duration. The BESS power/energy split is a rounded modeling decomposition benchmarked to Cole and Karmakar (2025), whose 2024 four-hour total is $334/kWh (about $1,336/kW against the model's implied $1,270/kW); with the 2.5% fixed-O&M fraction, the model prices storage slightly favorably, so the solar-entry thresholds in Section 5 are, if anything, conservative with respect to storage cost.

4.3. Core Equations

The LCOE for dispatchable generation is $\text{LCOE} = (\text{CAPEX} \times \text{CRF}(r,n) + \text{FOM}) / (8760 \times \text{CF}) + \text{VOM} + \text{FuelCost} + \text{CarbonCost}$ (1) with $\text{CRF}(r,n) = r(1+r)^n / [(1+r)^n - 1]$ (2), $\text{FuelCost} = (\text{HeatRate}/1000) \times P_{gas}$ (3), and $\text{CarbonCost} = (\text{HeatRate}/1000) \times (\text{EFCO}_2/1000) \times \text{PCO}_2$ (4). For the reference natural-gas combined-cycle (NGCC) plant (6,226 Btu/kWh), fuel cost is $24.90/MWh at $4/MMBtu and the carbon adder is about $33/MWh at $100/ton. The levelized cost of storage follows the LCOES formulation of Comello and Reichelstein (2019).

4.4. Multi-Market Capacity-Expansion and Storage Optimization

The core model co-optimizes investment and hourly dispatch as a linear program, run independently for each of the eleven markets on its real hourly solar profile. To retain tractability while preserving each market's true solar variability, each site's 365 daily 24-hour capacity-factor profiles are reduced to twelve representative days by k-means clustering (k=12, fixed seed), with each representative day weighted by its cluster size (weights sum to 365). This representative-period approach follows established capacity-expansion practice (Brown et al., 2018) and, unlike monthly averaging, preserves the real distribution of sunny, cloudy, and seasonal days.

Investment variables are the capacities of grid import, NGCC, photovoltaic (PV) generation, and a four-hour battery (power and energy). Wind, combustion turbines, and SMRs appear in Table 2 as levelized-cost screening context but are not investment variables; the optimization is deliberately confined to the technologies that define the gas-versus-firmed-solar margin the carbon-price sweep interrogates. Hourly variables are the dispatch of grid, NGCC, and PV; battery charge, discharge, and state of charge; PV curtailment; and penalized unserved energy. The objective minimizes annualized fixed cost plus weighted variable cost (grid energy at \$35/MWh; NGCC variable cost from Equation 1 including the carbon adder; a value-of-lost-load penalty on unserved energy). Constraints impose, in every representative hour, an energy balance; capacity limits on grid, NGCC (95% availability), and PV (bounded by the hourly resource, curtailable); battery power and energy limits; and state-of-charge dynamics with 85% round-trip efficiency and cyclic continuity within each representative day. A firm-capacity adequacy constraint requires that grid, firm NGCC, battery power (credited only at a minimum four-hour duration), and a small PV capacity credit meet peak load plus a 15% reserve margin. The model is implemented in Python (3.9 or later, with NumPy and pandas) and solved with the open-source CBC solver via PuLP; the complete code is openly archived (see Data Availability Statement). Because storage is priced and dispatch is temporally resolved, the model internalizes the cost of firming variable generation, the effect omitted by an annual energy balance and emphasized by the firming literature (Arbabzadeh et al., 2019; Comello and Reichelstein, 2019; Riepin and Brown, 2024; Tong et al., 2021). For each market, the model is solved across a sweep of carbon prices (\$0–250/ton) to locate the carbon-price threshold at which on-site solar first enters the optimal portfolio.

4.5. Monte Carlo LCOE Screening

As a screening complement, a Monte Carlo simulation draws 10,000 gas prices from a normal distribution (mean \$4.00/MMBtu, standard deviation \$1.50) clipped to the interval \$1.00–\$10.00/MMBtu and computes the NGCC LCOE at \$0, \$50, and \$100/ton (fixed seed 42). Clipping rather than truncating places 2.3% of draws (233 of 10,000) at the \$1.00/MMBtu lower bound and a single draw at the upper bound; this is the left-edge mass visible in Figure 2. Re-drawing from a truncated rather than a clipped normal raises the mean NGCC LCOE by less than \$0.50/MWh at every carbon price and changes no reported conclusion. This characterizes the levelized-cost competitiveness of gas versus a fixed PV LCOE; it is a screening device and does not determine the optimal portfolio, which is governed by Section 4.4.

4.6. Sensitivity Analyses

Three sensitivities test the robustness of the multi-market result. First, a PV-assumption case re-runs all markets with a more favorable utility configuration (DC-to-AC ratio 1.3, 11% system losses), which raises annual capacity factors by roughly 0.6–0.8 percentage points (3–4% in relative terms). Second, a temperature-responsive load case replaces the flat load with a facility load of the form $\mathrm{Load}(t) = \mathrm{IT} \times \mathrm{PUE}(T(t))$, where PUE is power usage effectiveness, IT = 160 MW, and $\mathrm{PUE}(T) = 1.2 + 0.006 \times \max(0, T - 20)$ capped at 1.5, using each market's real hourly ambient temperature; this raises cooling-driven load on hot afternoons and in hotter climates (mean facility load 193–198 MW across markets). Third, a grid-price case sweeps the flat grid import price from \$20 to \$75/MWh, spanning observed U.S. wholesale averages. All three are reported against the default headline rather than substituted for it.

5. RESULTS

Results are presented at five levels: levelized-cost screening; multi-market portfolio optimization; robustness to PV and load assumptions; a relaxed-grid counterfactual; and energy-efficiency implications.

5.1. Levelized-Cost Screening and Monte Carlo Results

At \$4/MMBtu gas and the EIA financing basis, deterministic LCOEs are approximately \$39/MWh (NGCC, \$0 CO_2), \$56/MWh (\$50), and \$72/MWh (\$100); PV (single-axis) is approximately \$63/MWh at a 25% capacity factor, consistent with Lazard (2025). Table 3 reports the Monte Carlo screening: the mean NGCC LCOE rises from \$39.3/MWh (\$0) to \$55.8/MWh (\$50) to \$72.4/MWh (\$100), and the probability that NGCC LCOE exceeds the \$63/MWh PV benchmark rises from under 1% to roughly 22% to roughly 84%. These are levelized-cost statistics only; they bound whether gas energy is dearer than PV energy per MWh but do not describe the optimal portfolio, because they omit the cost of firming PV to serve a continuous load and the site-specific solar resource. The portfolio question is addressed in Section 5.2. Figure 2 shows the simulated distributions against the PV benchmark.

Table 3. Monte Carlo screening of NGCC LCOE under gas-price uncertainty (10,000 draws).\

Carbon price	Mean (\$/MWh)	Median	P10	P90	Std. dev.	P(NGCC > PV \$63)
\$0/ton	39.3	39.2	27.1	51.3	9.2	~0.6%
\$50/ton	55.8	55.7	43.6	67.8	9.2	~21.6%
\$100/ton	72.4	72.2	60.1	84.3	9.2	~83.6%

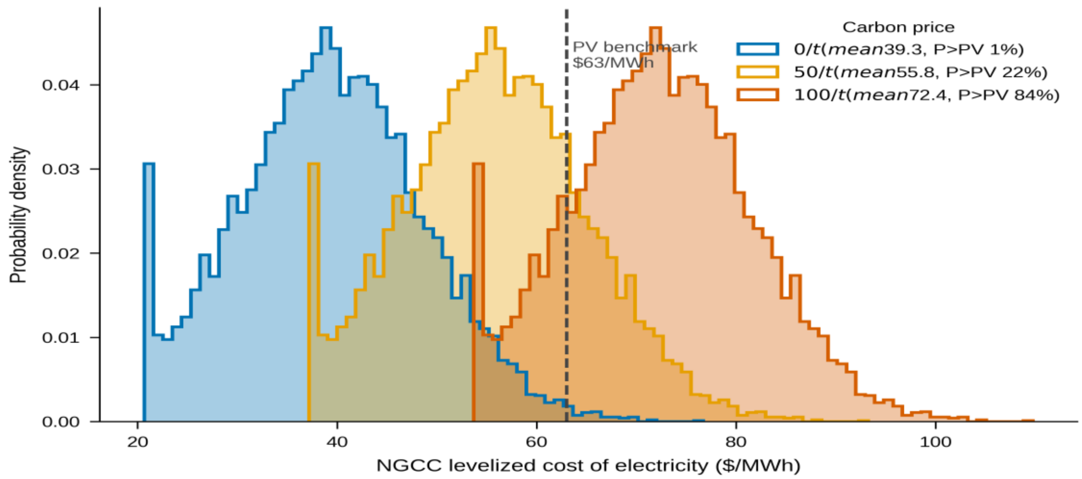

Figure 2. Distribution of NGCC LCOE under gas-price uncertainty at carbon prices of \$0, \$50, and \$100/ton (10,000 draws, fixed seed 42), against the \$63/MWh PV benchmark (dashed line). The panel reproduces the statistics in Table 3.

5.2. Multi-Market Portfolio Optimization

Table 4 reports, for each of the eleven markets, the real solar capacity factor, the carbon-price threshold at which on-site solar first enters the cost-optimal portfolio, and PV's energy share at \$150/ton. Across all markets and for carbon prices of \$0, \$50, and \$100/ton, the optimal portfolio is grid import plus dispatchable gas (NGCC ≈ 137 MW, adequacy-bound at the 200 MW flat load with a 15% reserve margin), with no on-site solar in any market at or below \$100/ton. Solar enters only above a high, market-specific threshold that ranges from approximately \$110/ton in the highest-insolation market (Phoenix) to approximately \$230/ton in the lowest (Portland). Even where solar enters, it supplies a minority of energy (at most about 18% at \$150/ton, in Phoenix) while gas remains the firm-capacity backbone.

Table 4. Multi-market optimization results: solar capacity factor, solar-entry carbon-price threshold, and PV energy share.

Market	Grid region	Solar CF	Solar-entry threshold (\$/ton)	PV % of energy @ \$150/ton
Portland, OR	Pacific NW	0.147	230	0%

Market	Grid region	Solar CF	Solar-entry threshold ($/ton)	PV % of energy @ $150/ton
Columbus, OH	PJM	0.168	190	0%
South Bend, IN	MISO	0.171	185	0%
Ashburn, VA	PJM	0.174	180	0%
Philadelphia, PA	PJM	0.175	180	0%
Charlotte, NC	Southeast	0.186	165	0%
Jackson, MS	MISO-South	0.188	160	0%
Atlanta, GA	Southeast	0.189	160	0%
Houston, TX	ERCOT	0.191	160	0%
Reno, NV	WECC	0.224	125	16%
Phoenix, AZ	WECC	0.238	110	18%

The threshold is a tight, monotonically decreasing function of solar capacity factor (Figure 3): a linear fit gives a coefficient of determination of R^2=0.97. The mechanism is transparent. Because dispatchable gas capacity is retained for firmness across all scenarios, on-site solar competes not against gas's full LCOE but against its variable cost (fuel plus carbon adder); solar therefore enters only when its levelized cost, which scales inversely with capacity factor, falls below the carbon-inflated gas variable cost. In low-insolation markets this requires very high carbon prices; in high-insolation markets it requires prices near $110/ton, still well above most current U.S. carbon policies.

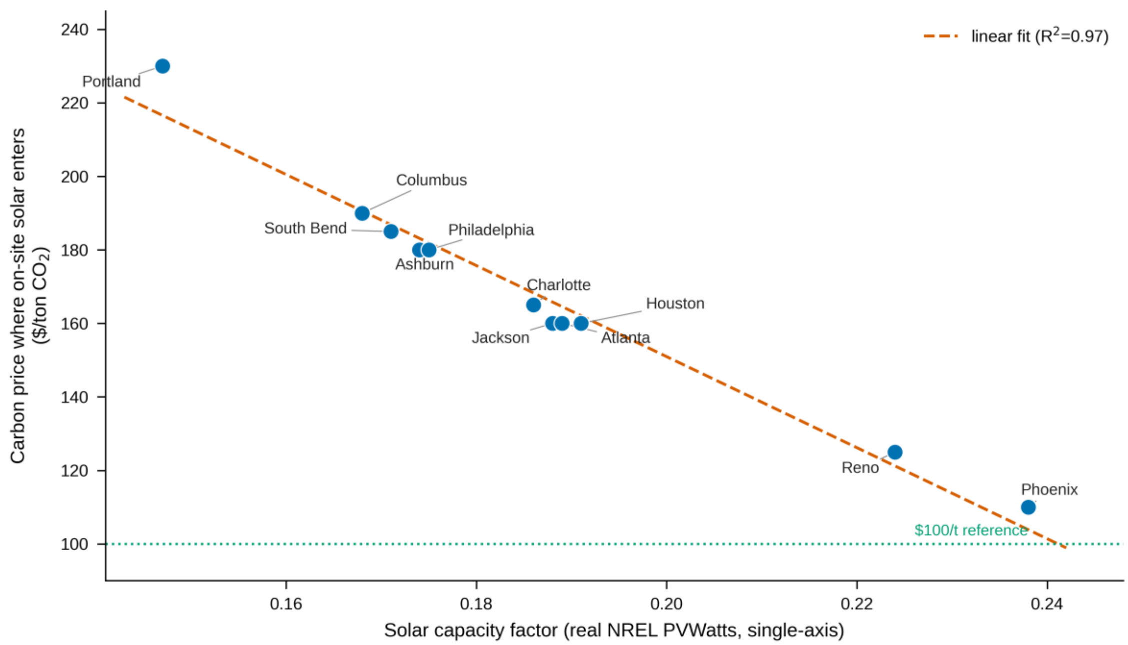

Figure 3. Carbon-price threshold at which on-site solar enters the cost-optimal portfolio, versus real solar capacity factor, across eleven U.S. data-center markets. The threshold scales monotonically with solar resource (R^2=0.97). The dotted line marks a $100/ton reference; no market crosses at or below $100/ton.

5.3. Robustness: PV and Load Sensitivities

The central result is robust to the most consequential modeling assumptions (Figure 4). Under the PV-assumption sensitivity (DC-to-AC ratio 1.3, 11% losses), capacity factors rise by roughly 0.6–0.8 percentage points and thresholds fall by only about $9/ton on average; even under these more favorable assumptions, no market's solar-entry threshold reaches $100/ton (the lowest, Phoenix, is $105/ton). Under the temperature-responsive load sensitivity, thresholds are essentially unchanged from the flat-load headline, because the additional cooling load, though larger in hotter markets and on hot afternoons, does not materially alter the balance between solar's levelized cost and gas's variable cost. The temperature-responsive load does change the capacity mix: peak facility load rises to roughly 204–218 MW, and NGCC capacity in Phoenix rises from 137 MW to about 159 MW, while the solar-entry thresholds are unchanged. The conclusion that gas is least-cost up to $100/ton in every market, and that the solar-entry threshold scales with resource, therefore holds across conservative and optimistic PV assumptions and across flat and temperature-responsive loads.

A third sensitivity tests the assumed grid price. Sweeping the flat grid import rate from $20 to $75/MWh leaves the solar-entry threshold identical to the reported value in all eleven markets up to $55/MWh, a span covering observed U.S. wholesale averages, and identical in nine of eleven across the entire range (Table S1). The invariance is structural: grid import is capped below campus load and is therefore fully dispatched, so the marginal supply decision lies between on-site solar and dispatchable gas, and the threshold condition contains gas's variable cost but not the grid price. Above roughly $60/MWh the behavior changes, because NGCC capacity expands beyond its adequacy requirement in order to displace grid energy; the enlarged gas fleet then competes with on-site solar, and the two highest-insolation markets shift by at most $15/ton and not monotonically. The flat grid price does bind on the relaxed-grid counterfactual of Section 5.4, where the break-even sits near $40/MWh and the null result is explicitly conditional on the assumed rate. A single flat rate is used across all markets by design: five of the eleven sit in vertically integrated territories without public hourly locational prices, and a uniform grid price preserves the property that only climate varies across sites.

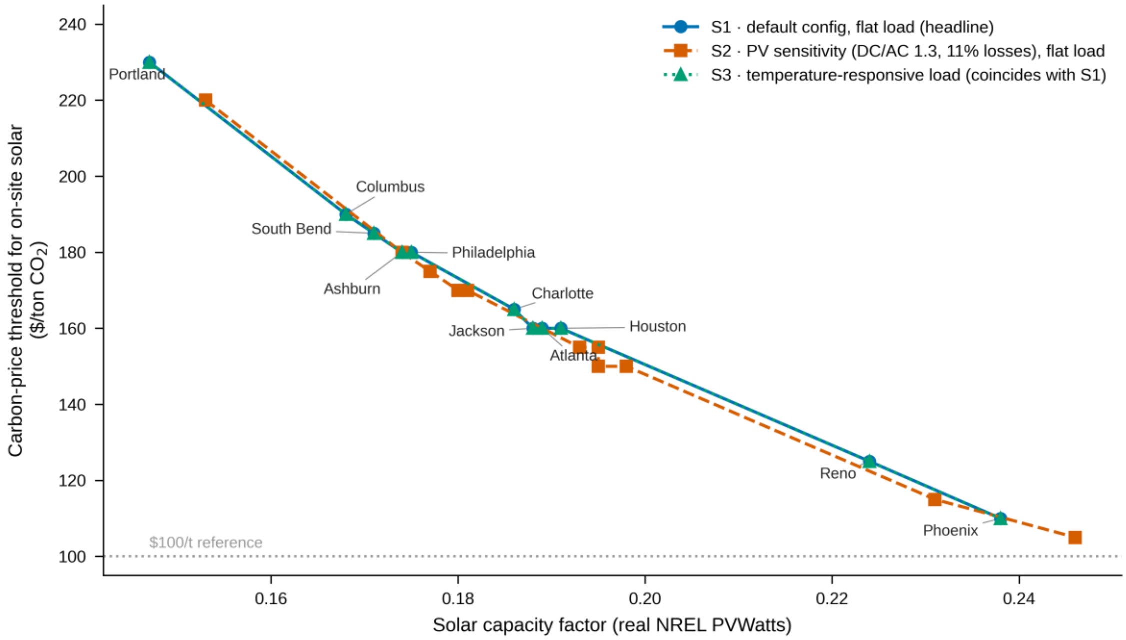

Figure 4. Solar-entry threshold across the eleven markets under three scenarios: default (PVWatts defaults, flat load), a PV-assumption sensitivity (DC/AC 1.3, 11% losses), and a temperature-responsive load. The curves nearly coincide, indicating the result is robust to both assumptions; no market crosses $100/ton in any scenario.

5.4. The Relaxed-Grid Counterfactual (H3)

H3 posits that BTM capacity retains value even without a binding grid constraint. Tested directly, the optimization gives a sharper answer, and it is null. Removing the import cap in steps (Phoenix, $0/ton) shrinks on-site gas from 137 MW at a 100 MW cap to 84 MW at 150 MW, 32 MW at 200 MW, and exactly zero at 230 MW (peak load plus the 15% reserve margin); no market builds PV in this counterfactual. The reason is structural. NGCC variable cost at $4/MMBtu is $28.23/MWh against the $35/MWh grid price (a saving of $6.77/MWh), while annualized NGCC fixed cost is $87,506/MW-yr, implying a break-even utilization of 12,933 h/yr, more hours than a year contains. Under the base assumptions, on-site gas can never pay for itself on energy arbitrage alone; the model builds it only because the import cap forces it for adequacy. On-site gas becomes viable on energy economics at a flat grid price of roughly $40/MWh (break-even 7,437 h/yr). H3's remaining support therefore rests on value streams outside the optimization: resilience, schedule option value, and hourly price volatility (Section 6.2).

5.5. Energy-Efficiency Implications

BTM selection has energy-efficiency consequences. Gas-fired BTM at the reference NGCC efficiency of about 54.8% produces recoverable waste heat that combined-heat-and-power (CHP) configurations could use to raise fuel utilization toward 70–80% where a co-located thermal sink exists; data-center thermal integration is nontrivial, so this is treated as a conditional opportunity rather than a modeled outcome. Delayed grid energization often forces reliance on temporary diesel generation at 30–35% efficiency, so timely BTM deployment is an indirect efficiency contributor. Because carbon accounting is temporally sensitive, operators pursuing 24/7 carbon-free-energy goals should evaluate hourly rather than annual matching (Miller et al., 2022; Riepin and Brown, 2024); the temporally-resolved framework here supports that evaluation.

6. DISCUSSION

6.1. Carbon Pricing and Portfolio Composition Across Markets (H1 and H2)

The multi-market optimization confirms H1 outright: absent carbon pricing, dispatchable gas is least-cost in all eleven markets. On H2, the results support a precise, conditional claim. Carbon pricing does move the portfolio toward on-site solar, but only above a high, resource-graded threshold ($110–230/ton), and never enough to displace gas as the firm backbone within the policy-relevant range; at $100/ton (already above most current U.S. carbon prices) gas remains least-cost in every market. This is exactly the outcome anticipated by the firming and reliability literature: solar cannot serve a continuous load without storage (Tong et al., 2021), storage cost often exceeds the value of shifted energy except under favorable conditions (Comello and Reichelstein, 2019; Petrollese, 2025), and 24/7 clean matching carries a premium reduced by firm resources (Arbabzadeh et al., 2019; Riepin and Brown, 2024). The near-perfect scaling of the threshold with capacity factor (Figure 3) provides a clean, generalizable relationship: the carbon price required to bring on-site solar into a data-center portfolio can be read directly from the local solar resource. The relationship is grounded in real hourly data across all eleven markets and is robust to the principal modeling assumptions (Figure 4).

6.2. The Counterfactual Relaxed-Grid Scenario (H3)

The relaxed-grid counterfactual (Section 5.4) rejects the strong form of H3: at the flat $35/MWh grid price, lifting the import cap removes all on-site build, because on-site gas cannot recover $87,506/MW-yr of fixed cost from a $6.77/MWh dispatch saving. The model's verdict is that under these assumptions BTM capacity is an adequacy instrument, not an arbitrage play. What survives is the weak form of the hypothesis. The roughly $40/MWh break-even sits close to the assumed grid price, so modest sustained price escalation, or the hourly price volatility a flat price cannot represent, restores on-site economics quickly. And the value streams the counterfactual cannot see are the ones driving current deployment: peer-reviewed evidence that interconnection completion is slow and uncertain (Gorman et al., 2024) gives owned capacity a schedule option value, and storage-economics and 24/7-procurement studies (Comello and Reichelstein, 2019; Riepin and Brown, 2024) show firm on-site resources are defensible where those constraints bind. H3 therefore stands as a qualitative proposition about resilience and schedule risk; on pure energy economics under a flat grid price, the null result stands, and hourly pricing is the extension that would test it further.

6.3. Equipment Lead Times as Binding Constraints (H4 and H5)

Table 1 and the peer-reviewed queue evidence support H4 and H5. Transformer lead times of 80–210 weeks (NIAC, 2024) and 36–60 months for large units (DOE, 2024c) rival or exceed generation construction schedules, and Gorman et al. (2024) confirm statistically that the interconnection process is a binding, cost- and time-intensive constraint. Because transformers and switchgear are required for every electrification pathway, the bottleneck cannot be avoided by switching generation technology. One caveat: the peer-reviewed evidence speaks most directly to interconnection timelines; the specific large-transformer figures rest on government and industry reporting.

6.4. Sensitivity to Fuel-Price Volatility

Gas-price assumptions move campus costs materially even without carbon pricing; the Monte Carlo P10–P90 band for NGCC LCOE at $0 carbon spans roughly $27–$51/MWh. Because carbon-price risk is largely unhedgeable whereas gas-price risk is partially hedgeable, the carbon exposure embedded in gas-heavy portfolios is a qualitatively different and arguably more concerning risk over long asset lives.

6.5. Limitations and Extensions

First, the model uses representative days, capturing intra-day but not multi-day low-resource periods; a full 8,760-hour chronology with long-duration storage would refine the firming result. Second, grid energy is a flat price without a carbon adder; hourly locational marginal prices and an economy-wide carbon signal would likely lower the solar-entry thresholds and are the most valuable data extension. Third, CHP potential is discussed but not modeled. Fourth, the analysis uses typical-meteorological-year solar data and a cost snapshot; learning-driven PV and battery cost declines (Cole and Karmakar, 2025; NREL, 2024) would lower thresholds over time. Fifth, market archetypes use representative metro coordinates rather than specific sites; results should be read as market-level rather than facility-level.

7. POLICY AND STRATEGIC IMPLICATIONS

For campus developers and operators, the results recommend treating time-to-power as a co-optimization across interconnection, transformer and switchgear procurement, and generation selection, with a two-track architecture: grid interconnection as the long-term backbone, BTM firm capacity as a schedule hedge. Carbon exposure should be quantified with heat-rate-based adders (Equation 4). Developers pursuing on-site solar should recognize that, at current carbon prices, gas remains least-cost for firm supply across U.S. markets, and that on-site solar becomes cost-optimal only at high, location-dependent carbon prices; high-insolation siting materially lowers that threshold (Figure 3).

For regulators and policymakers, the interconnection and equipment evidence points to two priorities: queue reform (DOE, 2024b; Gorman et al., 2024) and transformer supply-chain investment. The second lies outside interconnection reform and affects electric-vehicle charging, building electrification, and renewable interconnection alike. The finding that the carbon price required to shift data-center supply toward on-site solar is high and geographically uneven suggests that carbon pricing, storage-cost reduction, and high-insolation siting are complementary levers, and that carbon prices near current levels will not by themselves shift hyperscale supply away from gas.

For energy planning, predictable carbon-price trajectories would enable efficient staged investment, and storage-cost reduction is the lever most directly tied to lowering the solar-entry threshold at campus scale.

8. CONCLUSIONS

This paper has developed a multi-market framework for evaluating BTM power at hyperscale campuses under grid-capacity constraints, carbon pricing, and equipment lead-time uncertainty: levelized-cost screening coupled to a temporally-resolved, storage-inclusive optimization, run on real NREL solar data across eleven U.S. markets and reproducible from public inputs alone. Four conclusions follow. First, absent carbon pricing, dispatchable gas is the least-cost firm supply in every market. Second, and central to this study, dispatchable gas remains least-cost for carbon prices up to at least $100/ton in all markets, and on-site solar enters the optimal portfolio only above a high, resource-graded threshold ($110–230/ton) that scales tightly with solar capacity factor (R^2=0.97), supplying a minority of energy even where it enters; this holds across conservative and optimistic PV assumptions and across flat and temperature-responsive loads. Third, BTM power retains strategic value as a schedule hedge and resilience asset.

Fourth, transformer and equipment lead times, corroborated by peer-reviewed interconnection evidence, are a first-order constraint on feasibility. Future work should extend the model to full hourly chronology with long-duration storage, incorporate hourly locational grid prices, and formally model CHP; these extensions would sharpen and likely lower the solar-entry thresholds while preserving the geographic gradient established here.

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Ethics Statement This study involved no human participants, animal subjects, or personal data; ethical approval and informed consent were not applicable.

Data Availability All data are publicly available from the cited sources. Hourly solar-resource and temperature profiles were obtained from the NREL PVWatts V8 calculator using NSRDB PSM V3 typical-meteorological-year data for eleven public data-center market archetypes; the exact request parameters are documented in the Supplementary Materials, and the resulting profiles are archived with the code. The complete model code, the hourly input profiles, the model output files, the verification harness, and the figure-generation scripts are openly archived at Zenodo: https://doi.org/10.5281/zenodo.21803457, which always resolves to the most recent version. The exact release used to produce the results reported here is version 2.0.0: https://doi.org/10.5281/zenodo.22010318. The development repository is available online: https://github.com/dutta-sweta/btm-solar-threshold (accessed on 19 August 2026). Code is released under the MIT license and the accompanying data under CC BY 4.0.

Supplementary Material A single Supplementary Materials document is submitted with the manuscript, containing Figure S1 (equipment and interconnection lead-time evidence plotted against the typical campus construction window), the complete inventory of public data sources, the exact NREL PVWatts V8 request parameters, a data dictionary mapping every model input to its source and its entry point in the code, and step-by-step instructions for reproducing every reported result. The model code and data are archived separately and citably at https://doi.org/10.5281/zenodo.21803457.

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