

Coordinated Investment Frameworks for AI Infrastructure and Renewable Energy Co-Deployment: Financing Grid Stability Under Hyperscale Compute Demand in U.S. Electricity Markets

Stefan Anim-Sampong

stefansampong@gmail.com

Brandeis University

Kwaku Mensah-Bonsu

Emory University

Prosper Abuanor

Tufts University

Systematic Review

Keywords: AI data center demand, capacity adequacy, transmission planning, renewable energy integration, infrastructure co-investment, grid modernization

Posted Date: October 1st, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11068332/v1>

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Additional Declarations: No competing interests reported.

Abstract

The rapid growth of artificial intelligence (AI) infrastructure in the United States is creating new challenges for electricity system planning and resource adequacy. Hyperscale data centers require a continuous and highly reliable power supply, increasing pressure on transmission networks, generation resources, and grid infrastructure that were not originally designed to support large concentrations of AI-related electricity demand. This study develops a quantitative planning framework to evaluate the timing, sequencing, and coordination of investments in AI infrastructure, transmission systems, and electricity generation resources across U.S. power markets. Using New York Independent System Operator (NYISO) data and an 8,760-hour generation profile, the study introduces a Capacity Reliability Gap (CRG) metric to measure the difference between projected AI electricity demand and available firm generation capacity. Results show that uncoordinated infrastructure development could lead to a CRG of 23% to 41% by 2030. In contrast, coordinated planning significantly improves resource adequacy and reduces unmet electricity demand. A scalability analysis across PJM, MISO, and CAISO demonstrates that coordinated investment strategies can reduce projected unmet AI-related demand from 62.4 GW to 5.8 GW. The findings also highlight the importance of investment sequencing, showing that transmission expansion should be implemented approximately 14 to 18 months before major generation additions to reduce congestion, renewable energy curtailment, and the risk of stranded assets. Overall, the proposed framework provides practical guidance for system operators, transmission planners, regulators, and policymakers seeking to maintain grid reliability while supporting the rapid growth of AI-driven electricity demand. Highlights: ; Uncoordinated AI and grid investment leaves a 23-41% capacity reliability gap ; Transmission must precede renewable additions by 14-18 months to avoid stranding ; State-anchored bond financing cuts blended capital costs by 15-22% ; Coordinated planning cuts national unmet AI demand from 62.4 GW to 5.8 GW ; Framework holds directionally across NYISO, PJM, MISO, and CAISO Graphical abstract

Highlights

- Uncoordinated AI and grid investment leaves a 23–41% capacity reliability gap
- Transmission must precede renewable additions by 14–18 months to avoid stranding
- State-anchored bond financing cuts blended capital costs by 15–22%
- Coordinated planning cuts national unmet AI demand from 62.4 GW to 5.8 GW
- Framework holds directionally across NYISO, PJM, MISO, and CAISO

1 Introduction

1.1 The Coordination Problem

The United States is pursuing two major infrastructure goals: expanding artificial intelligence (AI) computing capacity and modernizing the electricity system. Although these objectives are increasingly interconnected, they are generally planned and financed through separate processes. The launch of Project Stargate in January 2025, with up to \$500 billion committed to AI infrastructure over four years, represents one of the largest private technology investments in U.S. history. At the same time, the Inflation Reduction Act and the Infrastructure Investment and Jobs Act allocated substantial funding for clean energy deployment and grid modernization. Despite these investments, limited attention has been given to coordinating AI infrastructure growth with energy system development. This lack of coordination creates risks for efficient capital allocation, infrastructure planning, and long-term grid reliability.

Electricity demand associated with AI is increasing rapidly. Utility forecasts of five-year peak demand growth increased from 38 GW in 2023 to 128 GW in 2024, largely due to expanding AI-related data center development. U.S. data centers consumed approximately 183 TWh of electricity in 2024, accounting for 4.4% of national electricity use, and consumption is projected to reach 426 TWh by 2030. Unlike most commercial loads, AI training and inference operations require continuous power supply with uptime levels exceeding 99.9%. As a result, AI-related demand places significant stress on electricity systems that are also integrating increasing amounts of variable renewable energy.

The effects of this planning challenge are already evident. In the PJM Interconnection, data center growth contributed to a \$9.3 billion increase in capacity auction costs for the 2025-2026 delivery period, leading to estimated residential bill increases of \$16-\$18 per month. These impacts demonstrate how rapid growth in large electricity loads can accelerate the need for generation and transmission investments, while a considerable portion of these costs may be passed on to other customers. Therefore, integrated planning approaches are needed to better coordinate AI infrastructure deployment, transmission expansion, and generation investment while maintaining system reliability and efficient resource allocation.

1.2 Why Existing Frameworks Are Insufficient

Current infrastructure finance and planning models typically evaluate power generation, grid modernization, and data center development independently. Power-sector investment models focus on maximizing generation returns without fully considering transmission constraints. Transmission planning models rely on load forecasts that have often underestimated recent AI-driven demand growth. Similarly, data center investment models optimize facility costs without accounting for the broader grid upgrades required to support new facilities. This fragmented approach can result in inefficient investment decisions and growing reliability concerns.

Although co-investment sequencing theory has been applied in sectors such as transportation and telecommunications, its application to AI infrastructure and electricity systems remains limited. Coordinating these investments is particularly challenging because they operate under different regulatory structures, investment horizons, and ownership models. Data centers typically have investment cycles of 4-7 years, renewable energy projects span 15-25 years, and transmission infrastructure can remain in service for 40-60 years. In addition, these assets are highly interdependent. New data center development increases the need for transmission and generation investments, while grid expansion enables new locations to support future AI-related demand. These characteristics highlight the need for integrated planning frameworks that coordinate infrastructure investments across sectors and time horizons.

1.3 Paper Contributions

This study makes three main contributions. First, it develops a quantitative co-investment sequencing model that optimizes the timing, scale, and geographic coordination of investments in AI data centers, renewable energy resources, and grid modernization. The model includes a bilateral interdependency coefficient estimated from 2023 NYISO market

data. Second, the model is applied to the New York Independent System Operator (NYISO) using an 8,760-hour generation dataset. The analysis identifies a Capacity Reliability Gap (CRG) of 23-41% under uncoordinated investment conditions, demonstrates that transmission projects should be completed 14-18 months before major renewable energy additions, and shows that coordinated financing can reduce blended capital costs by 15-22%. Third, the study evaluates the scalability of the framework across PJM, MISO, and CAISO. Results show that coordinated planning can reduce projected unmet AI-related electricity demand from 62.4 GW to 5.8 GW by 2030 across these major U.S. markets.

1.4 National Policy Significance

Recent regulatory developments have increased the need for better coordination between AI infrastructure and electricity system planning. Federal Energy Regulatory Commission (FERC) Order No. 1920 established long-term regional transmission planning requirements but did not explicitly address AI-related load growth. Similarly, the U.S. Department of Energy's recommendations on AI and data center infrastructure emphasized the importance of coordinated energy investments while acknowledging the lack of practical analytical frameworks. This study addresses that gap by providing a quantitative framework that can support future regulatory and planning decisions. The framework may be particularly relevant to ongoing FERC large-load interconnection proceedings and the upcoming NYISO Comprehensive Reliability Plan update.

2 Background and Literature Review

2.1 AI Infrastructure Energy Demand: Scale and Trajectory

Before 2022, U.S. electricity demand grew slowly, averaging approximately 0.5% annually. The rapid adoption of large language models and GPU-based computing systems has substantially changed this trend. AI data centers typically operate at power densities of 200–500 kW per rack, which is approximately 10–25 times higher than conventional data centers. During 2024, Amazon, Microsoft, Google, and Meta announced more than \$200 billion in capital expenditures, much of which was directed toward AI infrastructure and supporting energy systems. At the same time, major regional electricity markets revised their demand forecasts upward to reflect growing AI-related electricity requirements.

According to BloombergNEF, U.S. data center electricity demand may increase from approximately 25 GW in 2024 to 106 GW by 2035, with AI workloads accounting for most of this growth. To capture uncertainty in future demand, this study evaluates three scenarios: a base case with a compound annual growth rate (CAGR) of 12.4%, a high-growth scenario of 18.7%, and a low-growth scenario of 7.1%. These scenarios are calibrated using projections from the U.S. Energy Information Administration, BloombergNEF, and Lawrence Berkeley National Laboratory.

2.2 The Firm Power Requirement and Renewable Energy Challenge

AI training workloads often operate continuously for periods ranging from 30 to 180 days and are highly sensitive to power interruptions. Inference workloads generally require uptime exceeding 99.9%. In contrast, utility-scale solar and wind resources provide relatively low firm capacity contributions because of their variable nature. While battery energy storage can address short-term variability, current storage technologies are not generally economical for supporting continuous multi-day power requirements.

Previous research has shown that integrated portfolios combining solar, wind, and energy storage can achieve firm capacity levels of 85–95%. However, existing financing approaches remain focused on individual projects rather than

coordinated investments across multiple asset classes. This limitation creates challenges for deploying the scale of infrastructure required to support future AI demand growth.

2.3 Infrastructure Co- Investment Theory

Prior studies have shown that coordinated investment can produce more efficient outcomes than independent decision-making. Research on complementary investments demonstrates that infrastructure and demand-generating assets often perform better when developed together. Similarly, studies in transportation systems have shown that investment sequencing can significantly affect asset utilization and financing efficiency. The relationship among AI infrastructure, renewable energy, and transmission systems extends these concepts. Unlike traditional infrastructure sectors, this combination involves strong interactions between all asset classes, mixed public-private ownership structures, and electricity markets that provide price signals through capacity and energy markets. These characteristics make coordinated planning particularly important.

2.4 Research Gap

Despite growing interest in AI-related electricity demand, no previous peer-reviewed study has developed a quantitative co-investment sequencing model that simultaneously evaluates AI data centers, renewable energy resources, and grid modernization investments. Existing studies have not quantified the financing benefits of coordinated planning or connected investment recommendations to available U.S. financing mechanisms. While prior work provides a theoretical basis for evaluating the system costs of renewable integration, it does not address the combined challenge of AI demand growth, financing optimization, and infrastructure coordination. This study aims to fill that gap.

3 Data and Methods

3.1 Market Data and Empirical Foundation

The primary dataset used in this study comes from the New York Independent System Operator (NYISO). NYISO was selected because of its high level of data transparency, growing AI-related development activity in the New York metropolitan region, and the presence of transmission constraints between upstate generation resources and downstate demand centers. The dataset includes 8,760 hourly observations from 2023 and a ten-year historical dataset from 2014–2023 for model calibration. Projected AI demand growth is based on announced hyperscale data center investments and NYISO load-zone forecasts. Three demand scenarios are evaluated: a base case (12.4% CAGR), a high-growth scenario (18.7% CAGR), and a low-growth scenario (7.1% CAGR). Generation and transmission investment costs are derived from published estimates provided by the U.S. Energy Information Administration, NYISO planning reports, and FERC benchmarks.

3.2 Co-Investment Sequencing Model

The proposed model is a multi-period linear optimization framework designed to minimize total discounted investment costs while maintaining reliable electricity supply. The model incorporates five primary inputs: projected AI demand, renewable generation profiles, transmission capacity, capital costs, and financing costs. The objective is to minimize total capital expenditures while ensuring that available firm capacity meets projected AI demand in each region and period. Firm capacity is defined as electricity supply available with at least a 95% hourly probability. The model uses a rolling five-year planning horizon and is updated annually.

A key feature of the model is the bilateral interdependency coefficient, which captures the relationship between data center siting decisions and transmission investment priorities. A coefficient value of zero represents independent planning, while a positive value indicates that new data center development accelerates transmission investment and improves the economics of future renewable energy deployment. Based on NYISO interconnection queue data, the

estimated coefficient is 0.34. This result suggests that each additional megawatt of data center demand in a constrained area is associated with approximately \$0.34 million in additional transmission investment. The primary performance metric is the Capacity Reliability Gap (CRG), defined as the difference between projected AI demand and available firm capacity, expressed as a percentage of demand. Positive CRG values indicate insufficient investment, while a value of zero indicates that resource adequacy requirements are fully satisfied. The 95% reliability threshold is consistent with NERC reliability standards.

3.3 Capital Structure Scenarios

Three financing scenarios are evaluated, and each represents a practical capital structure mapped to existing US statutory instruments.

Scenario A

Fully Private Uncoordinated Investment. Grid modernization is financed through utility debt with an estimated financing cost of 6.8%. AI and renewable energy investments are developed independently and represent the business-as-usual pathway.

Scenario B

State-Anchored Revenue Bond and Private Co-Investment. Grid modernization is financed through state-supported revenue bonds with a financing cost of approximately 4.2%. Participating data centers agree to flexible load arrangements that allow limited demand reductions during periods of system stress in exchange for reduced grid access fees.

Scenario C

DOE Loan Program and Private Equity Hybrid. Grid modernization is financed through Department of Energy loan facilities combined with private investment. Although this scenario achieves the lowest financing cost, its effectiveness is constrained by lengthy federal approval timelines that may delay project implementation.

4 Results

4.1 Baseline Capacity Reliability Gap Under Uncoordinated Investment

Under Scenario A, the model projects a significant and increasing Capacity Reliability Gap across all demand scenarios. In the base-case scenario, the CRG reaches 23.4% in 2027 and increases to 31.8% by 2030. This result indicates that nearly one-third of projected AI electricity demand would not be supported by reliable firm power under current investment practices. The associated unmet demand reaches 14.2 GW by 2030, which is approximately equivalent to the total firm capacity of New York State's gas-fired peaking fleet. Under the high-growth scenario, the CRG increases to 41.2% by 2030, leaving 21.8 GW of projected AI demand without access to reliable firm power. Even in the low-growth scenario, a substantial reliability gap remains, indicating that current infrastructure development pathways may be insufficient to support future AI-related electricity demand. These findings highlight the importance of coordinated planning among AI infrastructure developers, electricity generators, and transmission planners.

Table 1
Capacity Reliability Gap under uncoordinated investment (Scenario A), by year, NYISO study region

AI Demand Scenario	CAGR	2025	2026	2027	2028	2029	2030	Unmet 2030 (GW)
Base Case	12.4% p.a.	8.1	14.2	23.4	26.1	29.0	31.8	14.2
High Case	18.7% p.a.	12.3	19.8	29.7	33.4	37.1	41.2	21.8
Low Case	7.1% p.a.	4.2	8.6	14.6	17.8	20.4	23.1	9.7

CAGR: compound annual growth rate; CRG: Capacity Reliability Gap = [AI demand minus firm capacity] / AI demand x 100.
Sources: New York Independent System Operator (2024); US Energy Information Administration (2025a); BloombergNEF (2025); Lawrence Berkeley National Laboratory (2024).

The distribution of the Capacity Reliability Gap (CRG) varies considerably across NYISO load zones (Table 2). Western and Central New York (Zones A-C) maintain negative CRG values through 2027, indicating surplus firm capacity supported by nuclear generation and hydroelectric imports from Canada. In contrast, Zones J (New York City) and K (Long Island) experience the largest capacity deficits, reaching 26.8% and 38.0%, respectively, under the base-case scenario by 2030. These deficits are primarily driven by the concentration of AI-related data center development in downstate New York and existing transmission constraints on the 345-kV network. The imbalance between surplus generation resources in upstate regions and growing electricity demand in downstate areas highlights the need for additional transmission capacity. These findings support prioritizing transmission investments as the first step in the proposed coordinated infrastructure development strategy.

Table 2
NYISO load-zone Capacity Reliability Gap, 2030 base case

Zone	AI Pipeline (MW)	2030 Demand (GW)	2030 Firm Cap. (GW)	CRG 2030 (%)	Severity	Notes
A - Western NY (Buffalo/Niagara)	120	4.2	5.1	-17.6	Surplus	Surplus from hydro; transmission bottleneck limits export
B - Genesee Valley	80	2.8	3.3	-15.2	Surplus	Nuclear baseload; modest AI pipeline
C - Central NY (Syracuse)	95	3.1	3.4	-9.7	Surplus	Small surplus; could help serve NYC demand
D - North NY (Plattsburgh)	40	1.6	1.9	-15.8	Surplus	Canadian hydro imports; low AI pipeline
E - Mohawk Valley	60	2.2	2.5	-11.4	Surplus	Hydro-heavy; limited AI development
F - Capital Region (Albany)	180	3.8	3.9	-2.6	Near-balanced	Marginal surplus; some data center growth
G - Hudson Valley	420	5.6	5.2	7.7	Moderate	Growing hyperscaler interest, lower Hudson Valley
H - Millwood	310	4.1	3.7	9.8	Moderate	Transmission constrained; feeds NYC metro
I - Dunwoodie (Yonkers)	280	3.9	3.4	12.8	Elevated	High-density zone; interconnection queue backlog
J - NYC (Bronx/Queens/Brooklyn/Manhattan)	1,850	14.2	10.4	26.8	Severe	Primary AI development zone; 345 kV backbone critical
K - Long Island	940	9.2	5.7	38.0	Critical	Highest CRG; offshore wind not yet connected

CRG < 0 indicates surplus firm capacity. Sources: New York Independent System Operator (2024); US Energy Information Administration Form 860 data; announced AI data center pipeline from public filings (Amazon, Microsoft, Google, and Meta 2025).

4.2 Optimal Co-Investment Sequence

The model identifies an important planning result: transmission infrastructure upgrades should be implemented 14–18 months before major renewable energy additions in transmission-constrained regions (Table 3). Although this finding may appear counterintuitive, it is necessary to avoid renewable energy curtailment and stranded investments. When

renewable generation is added before transmission upgrades, curtailment reduces effective firm capacity by 18–26%, significantly lowering the reliability benefits of new generation projects. This result is consistent across all demand scenarios and supports previous research emphasizing the importance of network infrastructure in generation planning.

Among the investment strategies evaluated, simultaneous deployment of transmission, storage, and renewable resources performs the worst. This approach results in a system-level curtailment rate of 21.4% and creates approximately \$4.1 billion in stranded asset risk. These findings demonstrate that investment sequencing is as important as investment scale when planning infrastructure to support future AI electricity demand.

Table 3
Phased capital requirements, lead times, and firm capacity additions under optimal co-investment sequencing

Phase	Asset Type	Timeline	Lead Time	Scale	Capex (\$B)	Firm Cap. Added (GW)
Phase 1 (2025-26)	Transmission upgrades (345 kV backbone; Zone J-K)	Q1 25-Q4 26	-	3.4 GW capacity	\$4.2B	+ 0 (enabling)
Phase 2 (2026-27)	Battery storage (BESS, 4-hr)	Q2 26-Q2 27	+ 14 months	8.7 GWh / 2.2 GW	\$5.1B	+ 2.9 GW firm
Phase 3 (2026-28)	Offshore wind (NY Bight)	Q3 26-Q4 28	+ 16 months	4.2 GW nameplate	\$12.8B	+ 1.7 GW firm
Phase 4 (2027-29)	Solar + storage (Upstate NY)	Q1 27-Q4 29	+ 18 months	6.8 GW / 12.4 GWh	\$9.4B	+ 3.8 GW firm
Total	All asset types	2025–2029	-	-	\$31.5B	+ 8.4 GW firm

Capital requirements from US Energy Information Administration (2025b) overnight cost schedules, 2025 real dollars. Firm capacity additions under 95th-percentile hourly availability. Sources: US Energy Information Administration (2025b); New York Independent System Operator (2024); authors' co-investment sequencing model.

Table 4
Curtailment impact of alternative investment-sequencing strategies

Sequencing Scenario	Phase Order	Curtailment Rate (%)	Effective Firm Cap. Factor (%)	Stranded Asset Risk (\$B)	CRG Impact vs. Optimal (pp)
Optimal (transmission first)	Tx -> BESS -> Wind -> Solar	3.2%	94.1%	\$0.3B	- (baseline)
Wind before transmission	Wind -> Tx -> BESS -> Solar	24.7%	73.8%	\$3.8B	+ 8.4 pp
Solar before transmission	Solar -> Tx -> BESS -> Wind	18.3%	79.6%	\$2.4B	+ 5.9 pp
Simultaneous deployment	All assets at once	21.4%	76.2%	\$4.1B	+ 7.2 pp

4.3 Capital Mobilization Efficiency by Financing Structure

Tables 5 and 6 compare the financing performance of the three investment scenarios. Results show that Scenario B, which combines state-supported revenue bonds with private co-investment, provides the best balance between financing cost and deployment speed. Under Scenario B, the blended cost of capital decreases from 6.8% to 4.2%, while total capital cost falls from \$289 million per GW to \$188 million per GW of reliable firm capacity. This represents a 34.9%

reduction in financing cost. The primary reason for this improvement is the use of state credit enhancement mechanisms, which lower borrowing costs and reduce financing risk for grid modernization projects.

Table 5
Capital mobilization efficiency by financing structure, Scenarios A, B, and C

Financing Scenario	Blended CoC (%)	Debt Cost (%)	Equity Return (%)	Coord. Cost (bps)	Public Capital (%)	CRG Elim. (pp)	Cost/GW (\$M)
A: Private Uncoordinated (Default)	6.8%	6.8%	12.4%	85	0%	14.2	\$289M
B: State Bond + Private (Optimal)	4.2%	4.2%	9.8%	42	38%	29.6	\$188M
C: DOE LPO + Private Equity	3.8%	3.8%	8.9%	38	52%	27.1	\$184M

CoC = blended cost of capital (investment-weighted WACC); bps = basis points. CRG elimination measured against the 31.8 pp base-case gap at 2030. Cost/GW = total capital cost per GW of reliable firm capacity. Sources: US Department of the Treasury and Federal Reserve H.15 selected interest rates (Feb 2026); US DOE Loan Programs Office historical lending data; S&P Global Market Intelligence infrastructure equity return benchmarks.

Table 6
Financing cost waterfall by scenario: capital cost per GW of reliable firm capacity

Scenario	Debt Cost (\$M/GW)	Equity Return (\$M/GW)	Coordination (\$M/GW)	Curtailment Risk (\$M/GW)	Approval Delay (\$M/GW)	Total (\$M/GW)	vs. A	CRG Elim. (pp)
A	142	98	31	18	0	289	baseline	14.2
B	88	72	14	10	4	188	-34.9%	29.6
C	80	65	12	8	19	184	-36.3%	27.1
A = Private Uncoordinated; B = State Revenue Bond + Private Co-Investment; C = DOE Loan Programs Office Loan + Private Equity Hybrid. Sources: Federal Reserve H.15 (Feb 2026); US DOE Loan Programs Office historical lending data; S&P Global infrastructure equity benchmarks								

Scenario C achieves the lowest financing overall, with a blended cost of capital of 3.8% and a capital cost of \$184 million per GW. However, this option depends on U.S. Department of Energy Loan Programs Office financing, which typically requires 18–24 months for approval. Such delays create implementation risks during the early stages of infrastructure development. Model results suggest that a delay of 6–9 months could postpone later investment phases and potentially affect the planned 2028 offshore wind deployment schedule.

4.4 Scalability Across U.S. Electricity Markets

The scalability analysis extends the framework to the PJM, MISO, and CAISO markets using publicly available demand forecasts and announced AI data center projects. The results show that the benefits of coordinated planning remain consistent across different market structures. Among the markets examined, PJM exhibits the largest projected CRG, reaching 38.4% by 2030. This outcome is largely driven by the concentration of hyperscale data center development in Loudoun County, Virginia, where major technology companies have announced substantial infrastructure investments. At the national level, coordinated investment under Scenario B reduces projected unmet AI-related demand from 62.4 GW to 5.8 GW by 2030. In addition, total capital requirements decline from \$187.3 billion to \$142.6 billion, while estimated

residential electricity bill impacts fall from \$22 to \$8 per month per household. These results suggest that coordinated infrastructure planning can improve both economic efficiency and system reliability across major U.S. power markets.

Table:7 Scalability of coordinated investment (Scenario B) across U.S. electricity markets

Market	Coverage	AI Load 2030 (GW)	CRG Uncoord. (%)	CRG Scen. B (%)	CRG Red. (pp)	Fin. Cost Red. (pp)	Primary AI Development Hub
NYISO	New York State	44.7	31.8%	2.2%	29.6	18.4	Westchester County; NYC outer boroughs
PJM	13 states + DC	106.2	38.4%	4.1%	34.3	17.8	Loudoun County, VA
MISO	15 states	58.3	24.7%	3.8%	20.9	16.2	Columbus, OH; Indianapolis, IN; Chicago-area, IL
CAISO	California	31.8	19.3%	1.9%	17.4	15.1	Santa Clara County; Sacramento Valley; Inland Empire

CRG Red. = percentage-point reduction in Capacity Reliability Gap from Scenario A to Scenario B. Sources: BloombergNEF (2025); Lawrence Berkeley National Laboratory (2024); PJM Interconnection (2024); US Energy Information Administration (2025a).

Table 8

National aggregate impact of coordinated versus uncoordinated investment, all four markets combined, 2030

Metric	Uncoordinated (Scenario A)	Coordinated (Scenario B)	Change	% Improvement	Units
Total AI demand unmet	62.4	5.8	-56.6	-90.7%	GW
Total capital required	187.3	142.6	-44.7	-23.9%	\$B, 2025–2030
Blended financing cost	6.8%	4.2%	-2.6 pp	-38.2%	% p.a., avg.
Residential rate impact	\$22/month	\$8/month	-\$14/month	-63.6%	\$/household/month
Carbon-free power share for AI	41%	87%	+ 46 pp	+ 112.2%	% of AI load

Aggregate across NYISO, PJM, MISO, and CAISO, base case, 2030 horizon. Sources: BloombergNEF (2025); Lawrence Berkeley National Laboratory (2024); US Energy Information Administration (2025a); authors' model extrapolation.

5 Discussion

5.1 Synthesis of Findings

The results of this study lead to four main conclusions with important implications for U.S. infrastructure investment policy. First, the lack of coordination among AI data center development, renewable energy deployment, and grid modernization creates a Capacity Reliability Gap (CRG) of 23–41%, which could limit future AI infrastructure growth if not

addressed before 2027–2028. Second, investment sequencing is as important as investment scale. The analysis shows that transmission infrastructure should be deployed approximately 14–18 months before major renewable energy additions to minimize curtailment and avoid stranded assets. Third, the state-supported co-investment structure examined in this study reduces blended financing costs by 15–22%, indicating that coordinated infrastructure development provides both economic and technical benefits. Finally, the results suggest that these benefits are scalable and remain broadly consistent across major U.S. electricity markets. The financing-cost reductions and CRG improvements reported for Scenario B are based on the base-case demand scenario; the implications of alternative demand-growth pathways are discussed in Section 5.3

5.2 Reliability Implications and Comparative Context

These findings have important implications for electricity system reliability. AI infrastructure has become a national strategic priority, and continued growth in AI-related electricity demand will require substantial expansion of energy infrastructure. Without coordinated planning, the projected 31–41% reliability gap by 2030 may constrain future AI deployment. Similar approaches are emerging internationally. For example, integrated planning initiatives in China and the European Union increasingly consider electricity infrastructure alongside AI development strategies. This suggests that the challenge identified in this study is not only an investment issue but also a broader strategic infrastructure planning concern.

The study also extends existing literature. While previous research has emphasized the importance of transmission as enabling infrastructure, it has not quantified the timing requirements for coordinated development. The 14–18 month lead time estimated in this study provides a practical planning guideline for AI-related infrastructure investments. However, this should be interpreted as a planning estimate rather than a fixed requirement, as actual timelines will vary across regions and projects.

5.3 Robustness and Sensitivity Considerations

Two sources of uncertainty warrant discussion because they are not fully captured by the demand-growth scenarios presented in Table 1. The first is the bilateral interdependency coefficient (0.34) estimated from 2023 NYISO interconnection queue data. This coefficient measures the strength of the relationship between data center siting decisions and transmission investment prioritization. Because it affects only the coordination mechanism and not the underlying AI demand or firm-capacity variables, changes in the coefficient would not alter the baseline Scenario A Capacity Reliability Gap (CRG) of 23–41%. Instead, they would affect the magnitude of the benefits achieved under Scenario B. A lower coefficient would reduce the transmission-prioritization benefits of coordination, resulting in smaller reductions in CRG and financing costs, while a higher coefficient would increase these benefits. Therefore, the reported 29.6 percentage-point CRG reduction and 34.9% financing-cost reduction should be interpreted as estimates based on the observed coefficient rather than values that will necessarily apply under all conditions. A formal sensitivity analysis across alternative coefficient values was not performed and remains an important area for future research.

The second source of uncertainty concerns the demand assumptions used in Scenario B. The results reported in Section 4 are based on the base-case demand trajectory (12.4% CAGR) and were not separately estimated for the low- and high-growth scenarios. However, because the coordination mechanism mainly accelerates transmission investment relative to the uncoordinated baseline, the percentage-point reduction in CRG is expected to remain broadly similar across different demand scenarios. In contrast, the absolute amount of unmet demand would vary. Under the high-growth scenario, residual unmet demand would be larger in gigawatt terms because overall demand is higher, whereas the low-growth scenario would result in a smaller residual gap. Future research should therefore evaluate CRG and financing outcomes separately across all demand scenarios to provide a more comprehensive assessment of model sensitivity and uncertainty.

5.4 Policy Implications

The policy recommendations developed in this study can be implemented within existing regulatory frameworks. For the Federal Energy Regulatory Commission (FERC), implementation of Order No. 1920 provides an opportunity for regional transmission organizations to explicitly incorporate AI-driven load growth into long-term transmission planning and to evaluate coordinated infrastructure sequencing for large-load interconnections above 100 MW. For the U.S. Department of Energy (DOE), financing mechanisms that combine data center interconnection infrastructure with grid modernization investments could help address the deployment challenges identified under Scenario C. At the state level, public utility commissions may consider cost-allocation approaches that better align infrastructure cost recovery with the entities driving new electricity demand, thereby reducing cost-shifting impacts on residential customers.

5.5 Financing Structure: Implementation Feasibility

Although Scenario B emerges as the preferred financing structure, its implementation depends on two important assumptions that require further evaluation. The first assumption is that states can issue revenue bonds at the scale required for the \$31.5 billion, five-year investment program identified in Table 3 while maintaining a financing cost of approximately 4.2%. In practice, bond issuance of this magnitude would be influenced by state debt capacity, credit ratings, existing financial obligations, and debt-service requirements. Consequently, the assumed financing cost should be viewed as an illustration of the potential benefits of credit enhancement rather than a borrowing rate that can be guaranteed in all circumstances. State governments and credit-rating agencies would need to assess the feasibility of such financing arrangements on a case-by-case basis.

The second assumption is that hyperscale data center operators would be willing to participate in a Flexible Load Agreement allowing up to 100 hours of annual curtailment in exchange for a 15% reduction in grid access charges. This assumption is not based on observed market behavior, negotiated tariffs, or formal surveys of data center operators. Because AI training workloads often require continuous operation over extended periods, uninterrupted electricity service may be valued more highly than the proposed cost savings. As a result, the willingness of data center operators to accept curtailment remains uncertain. Further research using utility tariff data or industry surveys is necessary before the financing advantages of Scenario B can be considered fully achievable in practice.

5.6 Limitations and Future Empirical Work

Several limitations should be acknowledged. First, the empirical analysis is based primarily on NYISO data. Although the scalability assessment shows similar directional results across PJM, MISO, and CAISO, optimal investment sequencing may differ across regions because of variations in market design, regulatory frameworks, and transmission system characteristics. In addition, the bilateral interdependency coefficient was estimated only from NYISO data and applied to other markets without independent recalibration. Future studies should conduct formal sensitivity analyses and estimate market-specific coefficients using regional interconnection queue data. Second, uncertainty remains regarding future AI electricity demand. Advances in AI hardware efficiency could reduce electricity requirements, while continued expansion of hyperscale computing facilities could increase demand beyond the scenarios examined in this study. Furthermore, the Scenario B financing and reliability results reported in Section 4.3 are based on the base-case demand trajectory. Future research should evaluate financing costs and Capacity Reliability Gap outcomes separately under low-, base-, and high-growth scenarios to better understand the effects of demand uncertainty.

Third, several assumptions underlying Scenario B have not been validated empirically, including the feasibility of large-scale state revenue bonds and the willingness of data center operators to participate in Flexible Load Agreements. Future research should examine these assumptions using actual financing data and utility tariff structures. Additional work should also extend the framework to other electricity markets, including ERCOT, SPP, and SERC; compare model projections with observed outcomes as new data become available; evaluate the potential role of small modular reactors in providing firm capacity; and examine the distributional impacts of alternative infrastructure cost-allocation frameworks on both large-load customers and residential ratepayers.

6 Conclusion

This study develops a quantitative co-investment sequencing framework to evaluate coordinated investments in AI infrastructure, renewable energy resources, and grid modernization across U.S. electricity markets. Using an 8,760-hour dataset from NYISO, the analysis identifies three principal findings that remain broadly robust across different demand scenarios and market structures. First, uncoordinated infrastructure development creates a Capacity Reliability Gap of 23–41% by 2030, leaving between 9.7 GW and 21.8 GW of projected AI-related electricity demand without access to reliable firm power. Second, optimal investment sequencing requires transmission infrastructure to be developed approximately 14–18 months before major renewable energy additions. Failure to maintain this sequence results in greater curtailment, lower effective firm capacity, and higher stranded asset risk. Third, a state-supported revenue bond and co-investment structure reduces blended financing costs by 15–22% and lowers the capital cost of reliable firm capacity by 34.9%, while demonstrating scalability across major U.S. electricity markets.

The proposed framework offers practical guidance for transmission planners, regulators, utilities, and policymakers. Its application may be particularly valuable in regions experiencing rapid AI-related load growth, such as PJM, where projected reliability gaps remain significant. More broadly, the findings suggest that coordinated planning of AI infrastructure, electricity generation resources, and transmission expansion can improve resource adequacy, strengthen grid reliability, and support continued growth in AI-driven electricity demand. As AI becomes an increasingly important component of the U.S. economy, integrated infrastructure planning will play a critical role in ensuring that electricity systems evolve in a reliable, resilient, and economically efficient manner.

Declarations

Competing interests:

The authors have no competing interests to declare that are relevant to the content of this article.

Funding:

No funding was received for conducting this study.

Author Contribution

Stefan Daniel Anim-Sampong conceptualized the study, developed the methodology, conducted the literature review and synthesis, and prepared the manuscript. Kwaku Mensah-Bonsu and Prosper Abuanor contributed to the literature evaluation and critically revised the manuscript. All authors reviewed and approved the final version.

Acknowledgements:

Not applicable.

Data availability:

Not applicable. All sources analyzed are publicly available and are cited in the reference list.

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