Storing the Future: A Modeling Analysis of Illinois Energy Storage Needs

Using the Open-Source Python for Power System Analysis Framework

HIGHLIGHTS

To estimate Illinois' anticipated energy storage needs to meet the clean energy goals of the Climate and Equitable Jobs Act, UCS created an open-source model of the Illinois electric grid. This technical appendix describes our modeling framework and provides details on the targets, scenarios, and key assumptions.

Technical Appendix

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Modeling Framework

To estimate Illinois' anticipated energy storage needs to meet the clean energy goals of the Climate and Equitable Jobs Act (CEJA),[1] we performed this analysis using the open-source modeling framework Python for Power System Analysis (PyPSA), a python environment for simulating and optimizing modern power and energy systems (Brown et al. 2024). As with other energy modeling frameworks, PyPSA formulates the optimization problem with linear programming, which minimizes an objective function representing the annualized system costs. In general, a linear program may be formulated as

Minimize

$$F(x) = \sum_i C_i x_i$$

subject to

$$g(x, p) \leq 0,$$
$$x \in \vec{X},$$

where

$\vec{X}$ = the set of decision variables,
C_i = the *i-th* cost,
g = some linear inequality constraint,
p = some arbitrary parameter.

The exact formulation is available in PyPSA's documentation (Brown et al. 2024). We developed a data pipeline to collect, process, build, solve, and plot a model of Illinois' electric grid and its results with the Snakemake workflow management tool (Mölder et al. 2021). A directed acyclic graph (DAG) of the workflow is provided in Figure 1. We hosted the model and its analysis on the GitHub platform to reflect the open-source, transparent, and publicly accessible nature of this project under a GPL-3.0 license (Dotson and Shaver 2024). Instructions to download and run the model are available on the GitHub repository.

[1] *Illinois Public Act 102-0662 (2021), https://www.ilga.gov/legislation/publicacts/102/PDF/102-0662.pdf.*

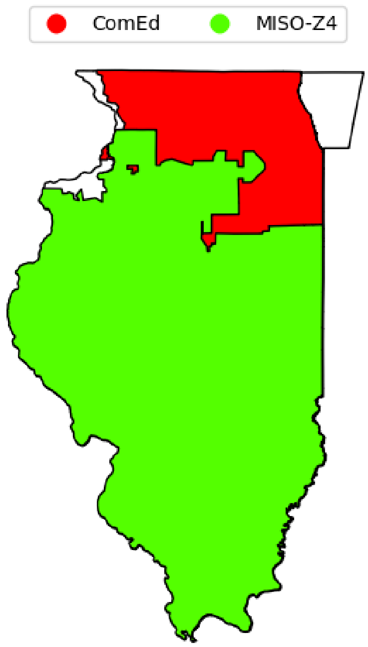
Figure 1. DAG of Snakemake Workflow

Modeled Region

For this analysis, we modeled the Illinois electric grid as two distinct regions representing the regional transmission organization (RTO) subregions of ComEd for PJM and Zone 4 for MISO. This model of Illinois was isolated from the rest of the MISO and PJM regions. Figure 2 shows the modeled regions.

Because load and generation were represented in the model as two distinct regions, we also needed to model renewable energy resources (specifically, wind and solar) as two distinct regions. This was done by calculating the geographic center of each modeled region and collecting representative wind speed and solar irradiation data for each. The geographic center was calculated by projecting the map onto the Albers equal area coordinate reference system, with EPSG code 5070, and then finding the centroid.

Figure 2. Map of the Modeled Regions in Illinois, ComEd (PJM) and Zone 4 (MISO)



Data Sources

All the input data used in this model came from publicly available sources and published research. All historical data, including energy demand, energy generation, emissions, and existing power plants, were sourced from the Energy Information Administration (EIA) using its application programming interface (API), version 2 (EIA 2024). We primarily drew cost data from the Annual Technology Baseline (ATB) of the National Renewable Energy Laboratory (NREL 2023). Table 1 shows the parameters we used for these data:

Table 1. Parameters for NREL's ATB

Version	Case	Scenario	Start Year	Cost Recovery Period
2022	Market	Moderate	2030	20

For the operating expenses of existing nuclear power plants, we used data from *Nuclear Costs in Context*, a publication from the Nuclear Energy Institute (NEI 2023).

For the fuel costs of coal and gas plants, we retrieved historical time series data from the EIA processed by the Public Utility Data Liberation (PUDL) project (Catalyst Cooperative 2024).

For solar and wind availability profiles, we accessed global horizontal irradiance (GHI) from the National Solar Radiation Database (NSRDB) of the NREL (Sengupta et al. 2018) and wind speed at 80 meters from the WIND Toolkit (WTK) of the NREL (King, Clifton, and Hodge 2014), respectively. For both wind and solar, we accessed data only for the geographic centers of each modeled region (as described previously). From the WTK, we downloaded data for the years 2009–13, and from the NSRDB, we downloaded data for 2016–20. For land-based wind turbines, we assumed all turbines performed identically and used the GE Vernova 2.75 MW turbine as a reference turbine (Bauer 2024). Table 2 describes the turbine parameters.

Table 2. Wind Turbine Operational Parameters

Cut-In	Cut-Out	Rated Speed (m/s)	Diameter (m)	Rated Power (MW)	Air Density (kg/m^3)
3.0	25.0	13.0	103	2.75	1.225

Data Processing

Solar and Wind Time Series Data

We used the GHI and wind speed data from NREL to estimate energy production profiles for solar and wind, respectively. Power from a fixed-tilt solar panel is given by

$$P_{solar} = GHI \cdot \tau_{pv}\eta_{ref}A[1 - \gamma(T - 25)]$$

where

τ_{pv} = the transmittance of the solar panel,
γ = the temperature coefficient,
A = the area covered by panels,
η_{ref} = the PV module efficiency,
T = the temperature in Celsius (Garcia et al. 2015).

However, we simplified this calculation by observing that solar power is directly proportional to GHI.

$$P_{solar} \propto GHI$$

Therefore, we can directly use the GHI from the NSRDB as an approximate energy production curve. Power from a wind turbine is given by

$$P_{wind} = \begin{cases} 0, & U < U_{in}, \quad U \geq U_{out} \\ \frac{1}{2}\eta\rho U^3\left(\frac{\pi D^2}{4}\right), & U_{in} \leq U < U_{out} \\ P_{rated}, & U = U_{rated} \end{cases}$$

where

η = the turbine efficiency,
ρ = the air density,
U = the wind speed at the hub height,
U_{out} = the cut-out speed for the turbine,
U_{in} = the turbine,
U_{rated} = the turbine's rated wind speed,
D = the diameter of the turbine blades (swept area),
P_{rated} = the rated power of the turbine.

Since turbine power has at least three operating regimes, we used the formula above to transform the wind speed to an approximate production curve. After generating the production curves, we converted them to availability curves by dividing each dataset by its L_∞-norm, which bounds all values in the time series between zero and unity.

For the wind turbines, we anticipate that future vintages will have higher average capacity factors due to improved technology and higher hub heights. To simulate this improvement over time, we further modified the wind turbine availability such that the average availability in each year reflects the capacity factor described in Table 3.

Table 3. Wind Turbine Availability

Vintage	Capacity Factor
Existing	0.3820
2030	0.3900
2035	0.3975
2040	0.4050
2045	0.4152
2050	0.4200

Fuel Cost and Time Series Data

The fuel cost data from PUDL had a monthly time resolution, whereas the model has an hourly time resolution. To convert the data to an hourly scale, we forward-filled the values such that the costs were the same for each hour within a single month. Additionally, the fuel cost data were provided in $/MMBtu, but PyPSA performs calculations in $/MWh. We converted the fuel cost data by multiplying by each technology's heat rate (in units of MMBtu/MWh).

Annual Capital Cost Calculation

Since PyPSA minimizes annual costs, we annualized the capital expenditure per megawatt ($/MW) reported in the ATB using the following annuity formula:

$$P_{capital} = \frac{r}{1 - \frac{1}{(1+r)^n}} \cdot PV$$

where

$P_{capital}$ = the annual capital payment,
r = the interest rate,
n = the number of payments (or the loan lifetime),
PV = the present value of the asset.

The total annual payment is

$$P_{total} = P_{capital} + C_{FOM}$$

where

C_{FOM} = the fixed operating and management cost ($/MW-year).

Since firms use a variety of financing tools—such as debt and equity—to realize a project, we used the weighted average cost of capital for each technology as calculated by NREL (2023). Additionally, we amortized the capital costs over the lifetime of the technology rather than over a uniform cost-recovery period since the technologies modeled here have a wide range of expected lifetimes.

Annual Electricity Demand

We used historical load shapes to model future periods using data from EIA. To simulate demand growth, we chose a starting demand level based on historical values and chose a growth rate; we then calculated a linearly increasing demand for each year using the formula

$$D(t) = r(t - t_0) + D_0$$

where

D_0 = the total electricity demand in the first modeled year,
r = the rate of demand growth,
t = the modeled year,
t_0 = the first modeled year.

We rescaled the historical load shapes by dividing each historical year by its sum (i.e., L_1-norm), making the sum equal to unity, then multiplied by the total electricity demand for each modeled year as calculated with the formula above.

Modeled Technologies

Instead of modeling individual power plants, we aggregated several technology classes. Table 4 shows the aggregated generators and some key assumptions about each.

The PyPSA framework builds technologies only if they are considered "extendable." Since CEJA calls for the retirement of power plants exceeding certain emissions standards, we excluded new fossil gas, coal, biomass, and carbon capture and sequestration (CCS) facilities.[2] As there are no current plans to build new light water reactors (LWR) or advanced nuclear reactors in Illinois, those were also precluded from new builds in the main results. We do note that, in December 2023, Illinois lifted its moratorium on new nuclear plants to allow small modular reactors of 300 MW or fewer beginning in 2026. While cost and performance data are currently highly speculative, it is possible such reactors could become commercially viable and receive operating licenses from the Nuclear Regulatory Commission (NRC). If that were to happen, for instance, in the later years of the model (i.e., after 2035), we would expect a reduction in the amount of storage needed to meet Illinois' carbon-free electricity goals in the years following 2035.

Table 4. Aggregated Technology Data

Technology	Full Name	Energy Carrier	Extendable	2024 Capacity (MW)	Lifetime (Years)	Incentive
CCAvgCF	Combined-cycle	Gas	No	6,008	40	None
CTAvgCF	Combustion turbine	Gas	No	12,897	40	None
IGCCAvgCF	Integrated gasification combined cycle	Coal	No	7,415	50	None
Biopower	Biopower	Biomass	No	0	60	ITC
Land-Based Wind	Land-based wind	Wind	Yes	7,902	20	PTC
Utility PV	Utility-scale photovoltaic solar	Solar	Yes	1,233	20	PTC
LWR	Light water reactor	Nuclear	No	12,415	80	None
NuclearSMR	Advanced nuclear	Nuclear	No	0	80	ITC
4Hr Battery Storage	4-hr battery storage	Batteries	Yes	95.6	20	ITC

Battery energy storage costs are modeled according to the ATB using lithium-ion batteries (LIB) as a proxy for energy storage costs generally. While other technologies exist in various

[2] *CEJA does allow the use of CCS at fossil units to comply with emissions limits, but the technology would need to achieve 100 percent capture (i.e., zero emissions). Currently, however, there is insufficient data available to model CCS at that level, as the NREL ATB does not include retrofit costs and "advanced" CCS options consist of only 90–95 percent capture rates.*

stages of development (Viswanathan et al. 2022), LIB is the most mature technology and the one most readily used in current and proposed projects today. We assumed that in any given year the lowest-cost technology will be built and that specific differences in operation between technologies are immaterial to the model.

Policy Incentives

The United States federal government introduced and extended several policy incentives for clean energy technologies following the Inflation Reduction Act (IRA) of 2022 and the Infrastructure Investment and Jobs Act, known colloquially as the Bipartisan Infrastructure Law (BIL), of 2021 (Steinberg et al. 2023). In this analysis, we modeled two policy incentives, a production tax credit (PTC) and an investment tax credit (ITC).

- Generators receiving a PTC are compensated for each MWh of clean energy produced at a rate of $30/MWh. We modeled this as a reduction in generators' marginal cost, which can be negative in some cases.

- Generators receiving an ITC receive a direct reduction in capital cost at a base rate of 30 percent, and up to 40 percent with bonus credits. We modeled a reduced capital cost of 40 percent for all technologies receiving the ITC.

Table 4 notes which generators received which policy incentive. The NREL report *Evaluating Impacts of the Inflation Reduction Act and Bipartisan Infrastructure Law on the U.S. Power System*, published in March 2023, goes into much more detail about the specifics of these laws.

Technology Constraints

To simulate scheduled plant retirements, we set a maximum energy generation limit for those retiring plant types. The maximum amount of energy that can be generated by fossil gas technologies is given by

$$E_{max} = (P_{2024} - P_{retirement}) \cdot N_{hours}$$

For example, in 2030, we expect 7.445 GW of fossil gas capacity to have come offline. Therefore, the remaining capacity is 18.905 GW less the 7.445 GW retirement. The maximum amount of energy that could be produced by this capacity is the remaining power times the number of hours per year (i.e., if the technology had a 100 percent capacity factor).

We also assumed that transmission between the two modeled regions was frictionless (i.e., free and unrestricted). In the near term, this is a reasonable assumption since MISO and PJM coordinate dispatch according to their Joint Operating Agreement, which is considered a model for other RTOs (Luo et al. 2014). Although the National Transmission Needs study indicates that PJM and MISO are behind on the build-out of transmission needed for a high-load, high-renewable future (DOE 2023), the two ISOs recently began a joint planning process to coordinate the build-out of new transmission, which may address congestion between the two regions over the long term (Howland 2024).

Scenarios

We identified a few parameters that were relevant to evaluating Illinois' storage needs. The first was whether Illinois maintains its status as a net energy exporter (Illinois Public Utilities Act – Renewable Energy Access Plan 2021).[3] Since Illinois is isolated from other regions in our model, we simulate this by setting the initial demand equal to the retail sales of electricity in Illinois or equal to the total in-state electricity generation for no-export or export cases, respectively. The second parameter was electricity demand growth. Table 5 describes the possible options for each parameter.

Table 5. Scenario Options for the Sensitivity Analysis

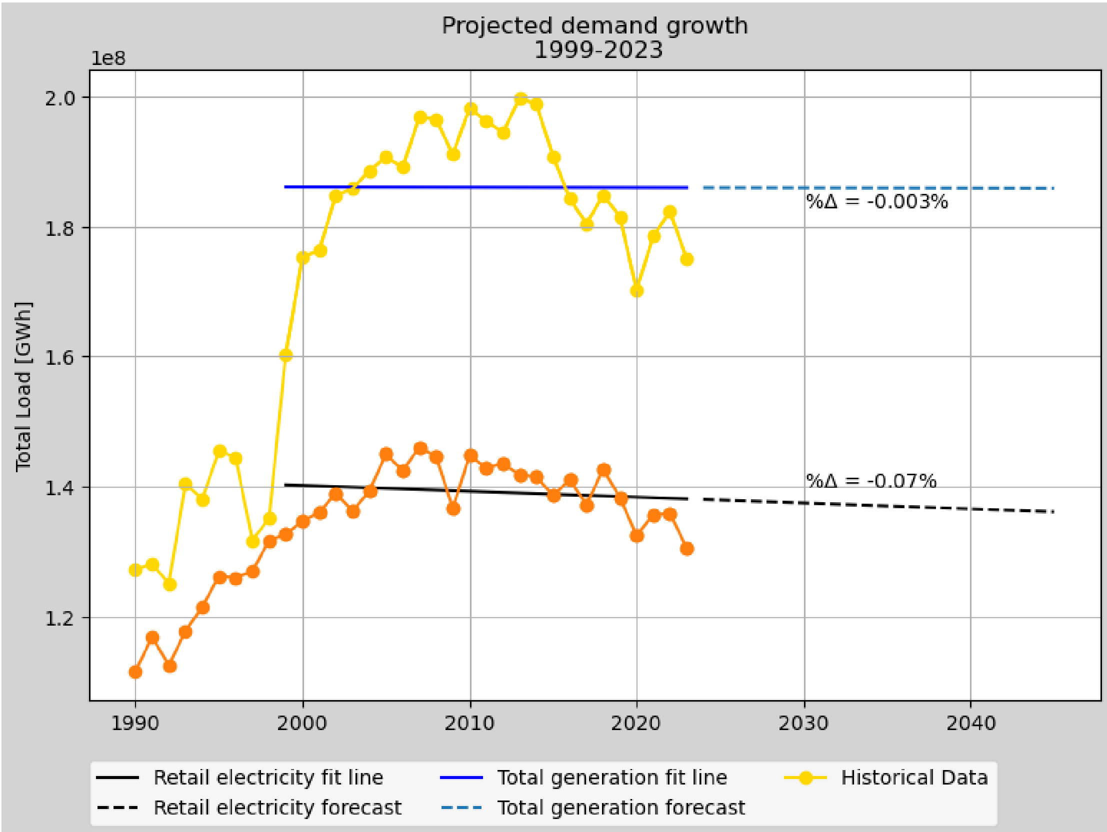
Initial Demand	Demand Growth (per year)
• In-state generation ("export") (185 TWh) • In-state retail sales ("No export") (140 TWh)	• Low growth (1%) • Expected growth (2%) • High growth (2.5%)

Demand Growth

We retrieved data on the supply and disposition of electricity in Illinois from EIA's "State Electricity Profiles" using its APIv2 (EIA 2024) for the years 1990 through 2023. Figure 3 shows this historical data. Although load growth has remained somewhat flat over the last 25 years, we expect a sharp increase in electricity demand following the needs of electrification and new loads from data centers and manufacturing. Previous work by PJM forecasted a 0.7 percent increase in load year-over-year for the ComEd region of PJM (PJM Resource Adequacy Planning Department 2024). However, sudden growth in data centers coupled with forecasted electrification from NREL's Electrification Futures Study suggests a somewhat higher future load growth (Mai et al. 2018). PJM also predicts a 2.4 percent increase across the entire RTO region. The high growth scenario aims to reflect this pattern in Illinois. Forecasting future load growth is precarious, so we present three load growth scenarios based on available predictions from NREL and PJM.

[3] *In 220 ILCS 5/8-512(a)(5), the Illinois General Assembly states the following: "The nation has a need to readily access this State's low-cost, clean electric power, and this State also desires access to clean energy resources in other states to develop and support its low-carbon economy and keep electricity prices low in Illinois and interconnected States."*

Figure 3. Historical Electricity Demand and Generation in Illinois Since 1990



Note: Shown is a best-fit line using data from 1999–2023.
SOURCE: Energy Information Administration (EIA) "State Electricity Profiles".

Results

Summary results are available through the project's landing page here: www.ucsusa.org/resources/storing-future. For the full results of the analysis, see here: https://doi.org/10.7910/DVN/7QRME4.

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