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Impacts of potential investments on electricity resource adequacy and emissions in Texas

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ABSTRACT

Growing demand, an increasingly variable power supply, and blackouts during a 2021 winter storm prompted the Texas legislature to incentivize the construction of dispatchable energy resources in the Electric Reliability Council of Texas (ERCOT) region. However, the absence of a comprehensive assessment of how different investment options affect both resource adequacy and emissions had left a gap in predicting the outcomes of the legislation. Here, two power system models were used to evaluate how potential investments in dispatchable generation, battery storage, transmission, or energy efficiency would affect resource adequacy and emissions in ERCOT. The Regional Energy Deployment System (ReEDS) model was used to project system capacity expansion under each scenario. Its outputs for the year 2030 were provided to the Python for Power System Analysis for the United States (PyPSA-USA) model to estimate hourly resource adequacy under historical weather conditions.

Model results indicate that adding dispatchable capacity and long-duration batteries would lead to more rapid closure of coal plants in ERCOT while slowing the growth of wind and solar only slightly, thus reducing greenhouse gas and air pollutant emissions and averting up to 100 premature deaths annually. Building transmission lines across regions would primarily accelerate the deployment of wind farms. Adding dispatchable capacity and improving energy efficiency would enhance resource adequacy during both winter and summer extreme weather events, while batteries are particularly effective during heat waves.

1. Introduction

The Electric Reliability Council of Texas (ERCOT), which manages the grid serving 90% of Texans, faces distinct challenges in enhancing electric reliability while reducing emissions. The isolation of ERCOT from the two grids that span the rest of the contiguous United States limits imports of power when extreme weather or other factors disrupt supply or escalate demand. Recent power outages and price spikes have highlighted ERCOT's vulnerability to disruptions from freezes [1], heat waves and droughts [2,3], natural gas supply shortages [4], power plant outages [5], and variable wind and solar output [6,7]. A severe winter storm in February 2021 [8] triggered shortfalls in power generation that left millions of Texas homes without power for multiple days [9,10].

Texas power plants emit more nitrogen oxides (NO_x), sulfur dioxide (SO_2), and carbon dioxide (CO_2) than those in any other state [11]. The NO_x and SO_2 emissions are estimated to cause hundreds of deaths per year by forming ground-level ozone and fine particulate matter (PM) [12], and the CO_2 contributes to climate change. Emissions reductions, especially at coal plants, may be needed to address regulations including nonattainment of ozone [13], SO_2 [14], and recently tightened PM standards [15] in several Texas regions; the Good Neighbor Plan from the Environmental Protection Agency (EPA) which would require steep NO_x reductions at power plants if it survives ongoing litigation [16]; an EPA-proposed regional haze plan that would require SO_2 controls at the largest two coal plants in ERCOT [17]; and EPA rules for CO_2 emissions that require coal plants to install carbon capture or retire by 2039 [15]. Unfavorable economics [18] and poor operational performance [19] make it likely that most coal plants would close or convert to natural gas if forced to reduce emissions.

As coal closures loom, Texas is projected to experience significant growth in electricity demand, driven by population and economic growth and the electrification of vehicles and heating [20,21]. ERCOT projects 1.5% to 2% annual growth in overall electricity demand over the next decade, and roughly 1% annual growth in peak demand [22]. However, the capacity of dispatchable power plants (i.e., units that can be turned on and off under variable weather conditions if properly maintained) has stagnated as closures of old plants have offset construction of gas plants. No coal, nuclear, hydropower, or geothermal

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plants are under construction, and most batteries provide only one to four hours of storage duration.

That has left two variable renewable resources — wind and solar — as the main sources of capacity additions in ERCOT. As of May 2024, ERCOT had 39.9 GW of wind and 24.9 GW of solar installed capacity alongside 14.7 GW of coal, 45.6 GW of natural gas combined cycle, 22.3 GW of other natural gas, and 5.3 GW of nuclear [23]. Historically, ERCOT recorded an all-time high demand of 85 GW in August 2023, while the average demand is approximately 50 GW [22]. Strong winds at inland sites at night and along the Texas coast on summer evenings help wind farms complement the output of solar farms, but there are hundreds of hours per year when it is neither windy nor sunny anywhere in ERCOT [24,25], and opportunities for hydropower are scant. Thus, it is essential to ensure that dispatchable resources plus variable wind and solar are sufficient to satisfy demand throughout the year. Although scenarios have been devised for operating electricity systems almost entirely on wind, solar, and storage alone [26,27], some studies find that retaining or even adding some lightly-used gas plants may reduce the costs of transitioning to high levels of wind and solar by reducing the amount of storage and transmission needed to balance them [28,29].

Previous studies have explored potential emission impacts of new generation, transmission, and storage in ERCOT. Deetjen et al. [30] found that the installation of 27 GW of wind and 11 GW of solar alongside 27 GW of transmission capacity could reduce CO_2 emissions by 65%. Kaffine et al. [31] found that new wind generation significantly reduces emissions of SO_2, NO_x, and CO_2. Other studies showed that connecting ERCOT to other grids with high-voltage direct current (HVDC) lines can lower the overall system costs, reduce emissions, and enhance system reliability and resilience [32–34]. The Interconnections Seam Study showed strong benefits for HVDC transmission connecting the Eastern and Western interconnections but did not consider connections to ERCOT [35], leaving a research gap that our study aims to fill. For storage additions in ERCOT, Craig et al. [36] quantified impacts on CO_2 emissions and Luo et al. [37] quantified health benefits.

As for grid reliability and resource adequacy, Medlock III [38] identified factors behind ERCOT outages during Uri, including derates across all major generation types, insufficient demand response, fuel supply chain failures, and DC interconnect shutdowns with neighboring regions. Hartley et al. [39] suggested enhancing reliability through investments in dispatchable generation, storage, and transmission expansion. Huang et al. [40] emphasized demand response to improve grid reliability, while Skiles et al. [41] found that improving energy efficiency in buildings could cut peak demand by nearly 30% during events like Uri.

Concerning the adequacy of electricity supply — especially in the wake of Winter Storm Uri — the Texas Legislature passed several bills in 2023 aimed at reshaping the state's energy infrastructure. Senate Bill 2627 provides financial incentives for new natural gas power plants, Senate Bill 785 clarifies the regulatory framework for geothermal energy development, and House Bill 1500 promotes the expansion of transmission infrastructure. These legislative actions mark a policy pivot toward firm, dispatchable generation following a rapid expansion of wind and solar capacity across Texas.

Advocates argue that natural gas offers more consistent, "on-demand" power than variable renewables, though critics note that increased reliance on fossil fuels may undermine long-term environmental goals. At the same time, new gas-fired capacity could accelerate the retirement of older, higher-emitting coal plants, potentially improving air quality—though the net emissions and health impacts of these shifts have not been comprehensively assessed. Although legislators have devoted less attention to demand-side solutions, a recent report from the American Council for an Energy-Efficient Economy [42] found that expanding energy efficiency and demand response programs could help balance the Texas grid faster and cheaper than building new power plants.

Although previous studies have assessed the role of individual technologies in addressing these challenges, a comprehensive evaluation of their combined impacts on emissions, health outcomes, and resource adequacy has not previously been conducted, particularly within the context of Biden-era legislation nationally and state legislation enacted in 2023. In this study, we address this research gap by examining how the addition of resources could transform the ERCOT grid. Particularly, we examine the changes in emissions and associated health impacts resulting from hypothetical resource additions influenced by recent legislative actions and infrastructure investments, shaped by federal initiatives such as the Inflation Reduction Act and Texas Senate Bill 2627 that was passed in 2023 in response to Winter Storm Uri of 2021. Overall, this study offers a timely and policy-relevant perspective on future grid planning in Texas.

In this study, we address this research gap by examining how the addition of resources could transform the ERCOT grid. Particularly, we examine the changes in emissions and associated health impacts resulting from hypothetical resource additions influenced by recent legislative actions and infrastructure investments.

To achieve this, we applied a capacity expansion model to model the reference case in 2030 with existing resources. We then modeled scenarios incorporating additional dispatchable generation resources (natural gas combustion turbines, natural gas combined cycle, or enhanced geothermal if it becomes viable); battery storage systems (2-, 4-, or 8-h duration); HVDC transmission links to the East and/or West Interconnection; and energy efficiency enhancements in ERCOT. Finally, we applied an operational power system model to assess how each scenario would affect hourly resource adequacy in ERCOT. While the models rely on simplified representations of electricity market dynamics and are only optimized for system-wide cost minimization, the resulting insights can inform efforts to reduce emissions and improve resource adequacy.

2. Methodology

The methodology used in this study is depicted in Fig. 1 and detailed in the subsections below. This study utilizes two primary models to evaluate the impact of resource additions on the ERCOT grid: the ReEDS (Regional Energy Deployment System) model and the PyPSA-USA (Python for Power System Analysis for United States) model. ReEDS is a state-of-the-art capacity expansion model, widely used in national reports to project future grid mixes under various policy and technology scenarios (e.g., Mai et al. [20]). In contrast, PyPSA-USA, although a relatively new model in the United States, has been extensively applied in European regions (e.g., Hörsch et al. [43]). PyPSA-USA complements ReEDS by simulating the detailed operational profiles of the grid with unit commitment attributes, particularly under extreme weather events, where high temporal resolution is necessary. The framework is summarized in the following steps:

1. Input data was compiled within ERCOT and nationally, including information on power plant characteristics, loads, and costs (Section 2.1).
2. Long-term capacity expansion modeling was conducted in ReEDS to estimate capacity, generation, emissions, and human health impacts under the baseline scenario (Section 2.1).
3. ReEDS was used to simulate plant builds and closures caused by each investment scenario including additions of dispatchable power plants (gas and geothermal), storage systems, HVDC transmission connections, and energy efficiency improvements (Section 2.2).
4. Outputs from the ReEDS scenarios were used in an operational power system model (PyPSA-USA) to estimate resource adequacy during extreme weather events in Texas (Section 2.3).

Appendix B presents an analysis of historical and future dispatchable reserves on a monthly and hourly basis. This analysis highlights the transition of peak demand periods from summer afternoons to nighttime hours.

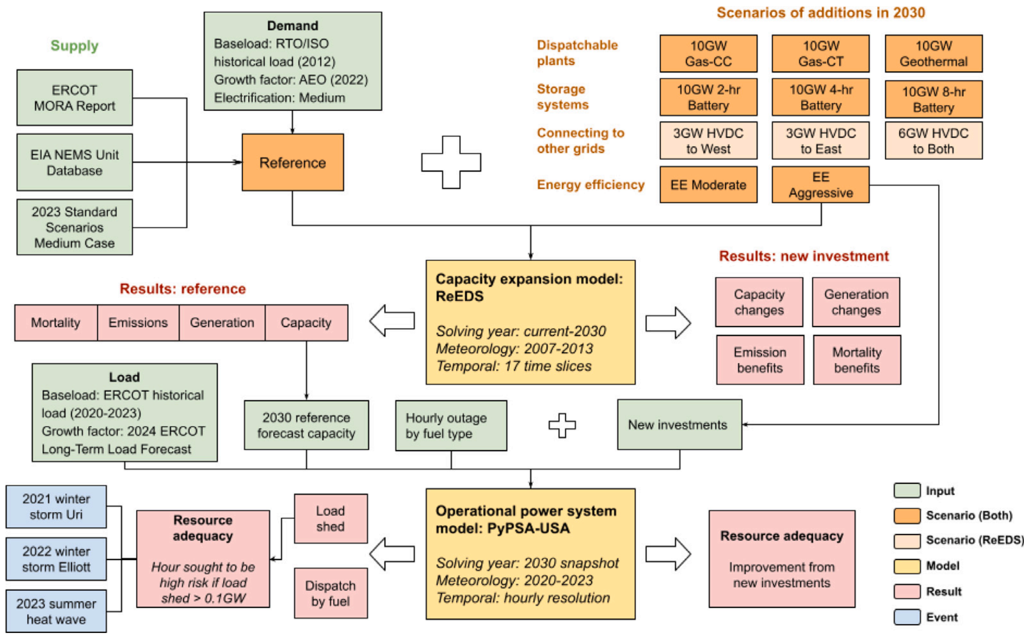

Fig. 1. A schematic representation of the methodology used in this study.

2.1. Capacity expansion model

The Regional Energy Deployment System (ReEDS) model Version 2022 is a long-term capacity expansion model developed by the National Renewable Energy Laboratory (NREL) to model the evolution of electric systems in the contiguous United States (CONUS) [44,45]. It is a myopic optimization model that optimizes capacity expansion decisions iteratively, considering near-term system conditions rather than predicting future changes in conditions. The model considers a wide range of technology options, including multiple types of coal and natural gas generators, nuclear, biopower, photovoltaic, concentrating solar power, onshore and offshore wind, hydropower, and geothermal as well as energy storage and transmission expansion options.

ReEDS simulates supply, demand, and transmission across 134 balancing areas (BAs) nationally, including 7 BAs in ERCOT (Fig. 2, left). Transmission between BAs is represented by line limits (MW) reported by the North American Electric Reliability Corporation (NERC). ReEDS categorizes hours into 17 time slices: overnight, morning, afternoon, and evening in each of four seasons, and "summer superpeak" for the 40 h with the highest summer load. Load is defined exogenously based on scenarios from Annual Energy Outlook (AEO) 2022 [46] and apportioned to the 17 time slices in each BA. More information on estimating future loads is described in Ho et al. [44].

Here, the objective function in the model was solved annually from 2010 to 2030. In each year, the model minimized the net present value of the nationwide electric power sector costs using linear programming. In the years 2010–2022, ReEDS takes exogenous prescribed builds from the ERCOT Monthly Outlook for Resource Adequacy (MORA May 2024) generator profile for the ERCOT region of Texas [23] and the EIA NEMS unit database [46] for the rest of country.

Cost and performance assumptions for new power plants were derived from the NREL Annual Technology Baseline (ATB) 2023, which provides cost projections for a range of conventional and renewable technologies, accounting for potential technological advancements and policy changes [47]. In this study, the moderate scenario was selected to represent expected technology innovations and trends in the future. For renewable energy resources such as wind, solar, and geothermal, resource supply curves were used instead of fixed cost assumptions, as the costs of these technologies are highly spatially dependent [44]

The model categorizes natural gas generators as combined cycle (Gas-CC) or combustion turbine (Gas-CT). We grouped existing oil and gas steam generators with Gas-CT plants because of their similar efficiencies, which are smaller than those of Gas-CC plants. Our ReEDS modeling assumed that all gas plants operate with 5% forced outage rates year-round, with no planned outages during the summer, and with planned outage rates of 10% for Gas-CC and 7% for Gas-CT during other seasons.

ReEDS considers multiple types of geothermal resources, but only deep enhanced geothermal systems (EGS) are applicable in Texas due to its lack of hydrothermal resources. To date, EGS is prohibitively expensive under base case assumptions. However, the U.S. Department of Energy (DOE) Enhanced Geothermal Shot initiative is targeting deep reductions in EGS costs DOE [48]. Four solar photovoltaic technologies — utility-scale photovoltaics (UPV), distribution-side utility-scale PV (DUPV), rooftop PV, and hybrid photovoltaics-battery system (PVB), as well as concentrating solar power (CSP) — were considered, along with land-based and offshore wind power. ReEDS models five options for battery systems, with durations ranging from 2 to 10 h [27]. The only HVDC transmission connections modeled by ReEDS between ERCOT and neighboring grids are 220 MW from Northwest Texas to Oklahoma and 600 MW from the Dallas region to the Northeast Texas region managed by Southwest Power Pool (SPP).

The model allows endogenous investments and retirements beginning in 2024. Planned capacity builds in future years are prescribed as a lower bound for new investments, i.e., the model must build at least the prescribed amount. The baseline planned capacity levels are based on NEMS planned generator profiles [46]. Since actual and planned solar, wind and battery projects tracked by ERCOT far exceed what NEMS modeled before 2027, we updated the prescribed builds of UPV, wind farms, and storage using the Monthly Generator Interconnection Status Report (Dec 2022) from ERCOT, counting only projects with a signed interconnection agreement, financial security posted, and a notice to proceed provided [49]. Table 1 shows the 2022 end-of-year capacity for main plant types, and prescribed capacity from 2023 to 2025. The base scenarios, or Reference, were modeled based on the updated generator profile, with default inputs from the NREL Mid-case scenarios [45].

ReEDS outputs annual emissions rates of each criteria pollutant and greenhouse gas. Through the post-processing step, it also estimates region-specific health damages from power plant NO_x and SO_2 emissions via their impacts on ground-level ozone and particulate matter using three reduced-complexity models: AP2 [50], EASIUR [51],

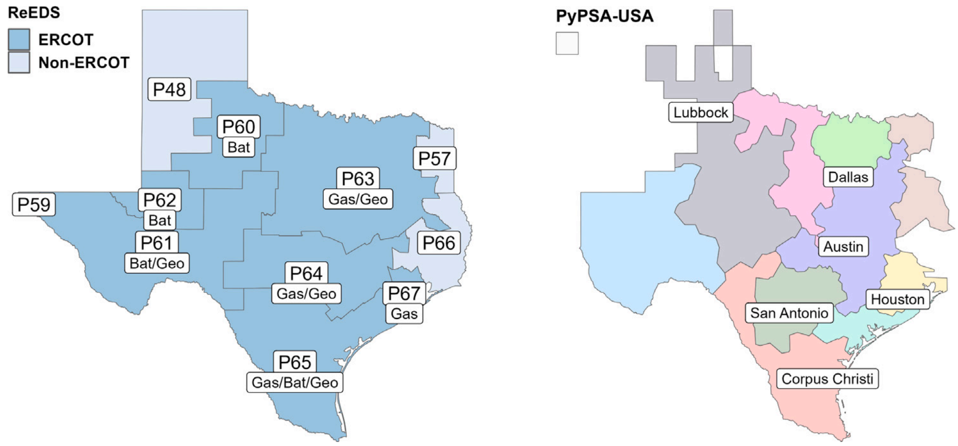

Fig. 2. **Left:** The balancing areas (BAs) in Texas in ReEDS, with dark blue indicating areas managed by ERCOT. **Right:** Regions used in PyPSA-USA modeling.

Table 1
Capacity by fuel in ERCOT at the end of 2022 as well as the planned additions from the ERCOT interconnection queues in Dec 2022 [49]. For coal, gas-CC, and gas-CT, the emission rates (kg/MWh) of CO_2, SO_2, and NO_x are estimated from Texas Commission on Environmental Quality (TCEQ) emission inventory in 2021.

Tech	2022 capacity (MW)	Planned additions by 2025 (MW)	Emission rate (kg/MWh) CO_2	SO_2	NO_x
Coal	15,533	–	1062	1.45	0.52
Gas-CC	34,127	670	465	0.002	0.075
Gas-CT	20,951	1,222	627	0.005	0.206
Nuclear	5,268	–	–	–	–
Others	1,964	–	–	–	–
Storage	2,788	7,987	–	–	–
UPV	14,122	25,079	–	–	–
Wind	35,646	8,213	–	–	–

and InMAP [52]. Recent studies found that these reduced-complexity models simulate health impacts consistently with each other and with three-dimensional air quality models [53–55]. In this study, we average the damage estimates across the three models.

2.2. Resource addition scenarios

Table 2 summarizes the scenarios modeled in this study, including building new dispatchable power plants, battery systems, HVDC transmission lines connecting ERCOT to neighboring interconnections, and energy efficiency improvements. All are assumed to be implemented in 2030.

The scenarios with additions of gas and geothermal assumed that 10 GW is added to the prescribed builds in 2030. We focus on 10 GW since it is the amount sought by Senate Bill 2627. Developers have since filed notices of intent to apply to the Texas Energy Fund for financing to support 56 GW of new gas generation [56], but we expect that only a small fraction of those projects will come to fruition.

New gas power plants, either *Gas CC* or *Gas CT* were assumed to be equally apportioned to each of the four ERCOT BAs with closest proximity to urban and industrial load: P63, P64, P65, and P67 (Fig. 2). Unlike gas plants, which have relatively uniform costs across locations, the capital costs for geothermal plants are strongly influenced by the geothermal quality at the site. Therefore, new geothermal capacity (Geo), if it becomes viable, is assumed to be sited in the four ERCOT regions with the most favorable geothermal temperature gradients: 1553 MW in P61, 15 MW in P63, 783 MW in P64, and 7649 MW in P65 [57].

New battery sites (*2* h *Bat*, *4* h *Bat*, and *8* h *Bat*) are apportioned equally to the four BAs listed in Table 2 where the highest curtailments of wind and solar were found in ReEDS modeling of 2030 under the reference scenario. Here, we consider 2- and 4-h duration batteries to represent two commonly deployed options and 8-h batteries to examine the impact of longer storage durations. Fuel prices were taken from the reference case of the EIA Annual Energy Outlook 2022 EIA [46], except for natural gas capacity expansion scenarios that considered high and low natural gas prices from that outlook.

The transmission scenarios in our study follow the locations of two HVDC lines proposed to connect ERCOT with neighboring grids. Developers of the Southern Spirit Transmission Project have proposed to construct a 3000 MW merchant tie between ERCOT and the Eastern Interconnection using a 320-mile HVDC line [58]. Grid United Texas has proposed to construct a Pecos West HVDC Intertie providing 1500 MW to 3000 MW of HVDC transmission via a 280-mile line from ERCOT to the West Interconnection near El Paso [59]. In this study, we assume each project would add a 3 GW HVDC line in 2030 and name the scenarios *Trans East* and *Trans West* based on the region they would connect to. A *Trans Both* scenario assumes both lines would be built.

Two scenarios focused on energy efficiency improvements across residential, commercial, and industrial sectors C. For the residential sector, we extracted the electricity use data from White et al. [21], showing standard, high, and ultra-high efficiency heating and cooling scenarios on an hourly basis. Energy savings for the moderate (*EE MOD*) and aggressive (*EE AGG*) scenarios were calculated by comparing standard to high and ultra-high efficiency scenarios, respectively. Each hour was assigned to one of 16 time slices, and the top 40 peak demand hours in the summer afternoon were categorized as the summer peak time slice. Statewide energy savings were allocated to counties based on population and then aggregated to ReEDS regions. Commercial sector impacts were assumed to be half that of the residential sector based on Rhodes et al. [60].

Industrial energy efficiency scenarios were derived from the U.S. Energy Policy Simulator (EPS) Nationally Determined Contributions (NDC) scenario, following the U.S. Paris Agreement commitments [61].

Table 2
Scenarios modeled for additions of gas or geothermal power plants, battery storage, transmission, and energy efficiency modeled in ReEDS.

Scenario	Short name	ReEDS BAs for deployment	New capacity prescribed	Related policy
Reference	*REF*	–	–	–
10 GW CC	*Gas CC*	P63 (North Central) P64 (South Central) P65 (South) P67 (Coast)	2.5 GW Gas-CC in each BA	SB 2627
10 GW CT	*Gas CT*	P63 (North Central) P64 (South Central) P65 (South) P67 (Coast)	2.5 GW Gas-CT in each BA	SB 2627 HB 1500
10 GW Geothermal	*Geo*	P61 (Far West) P63 (North Central) P64 (South Central) P65 (South)	1.6 GW EGS in P61 0.015 GW in P63 0.8 GW in P64 7.6 GW in P65	SB 2627 SB 758 DOE enhanced geothermal shot
10 GW 2 h Battery	*2 h Bat*	P60 (Northwest) P61 (Far West) P62 (West) P65 (South)	2.5 GW 2 h Battery in each BA	IRA storage tax credit
10 GW 4 h Battery	*4 h Bat*	P60 (Northwest) P61 (Far West) P62 (West) P65 (South)	2.5 GW 4 h battery in each BA	IRA storage tax credit
10 GW 8 h battery	*8 h Bat*	P60 (Northwest) P61 (Far West) P62 (West) P65 (South)	2.5 GW 8 h battery in each BA	IRA storage tax credit
Transmission: 3 GW to West	*Trans West*	P59-P61 (Connect West)	3 GW HVDC (P59–P61)	Proposal from grid united texas
Transmission: 3 GW to East	*Trans East*	P57-P63 (Connect East)	3 GW HVDC (P57–P63)	Southern spirit transmission project
Transmission: 6 GW to Both	*Trans Both*	P59-P61 (Connect West) P57-P63 (Connect East)	3 GW HVDC (P59–P61) 3 GW HVDC (P57–P63)	Proposal from Grid United Texas Southern Spirit Transmission Project
Energy efficiency: Moderate	*EE MOD*	ERCOT	1.6 GW average reduction in demand	IRA rebate programs
Energy efficiency: Aggressive	*EE AGG*	ERCOT	3.0 GW average reduction in demand	IRA rebate programs

The aggressive case used the NDC percentage reduction, while the moderate case used half that percentage. The EPS tool estimated electricity savings with a 7% efficiency improvement by 2050 for *EE MOD* and 14% for *EE AGG*. Enhanced material efficiency and re-use policies from the NDC scenario would lead to a 5% reduction in cement demand and a 7% reduction in iron and steel demand by 2050 in the moderate case, and a 10% and 15% reduction respectively in the aggressive case. The simulator then estimated the updated electricity use trendline from 2020 to 2050, and we extracted projected electricity use for the year 2030. More details on compiling energy efficiency scenarios are included in Appendix C.

Electricity demand reductions in the industrial sector were spatially resolved by using county-level electricity usage data from McMillan and Narwade [62] for each North American Industry Classification System (NAICS) category and then aggregating to ReEDS regions. Percentage reductions in industrial electricity use were assumed to be uniform throughout the year.

2.3. Operational power system model

The Python for Power System Analysis for the United States (PyPSA-USA, https://pypsa-usa.readthedocs.io/en/latest/) model was used to model hourly dispatch in order to examine resource adequacy during high-demand events. We modeled meteorology from weather years 2020 to 2023, which featured multiple periods of extreme weather including winter storm Uri, which led to major blackouts in February 2021 [19,63], winter storm Elliott in December 2022 [64] and a record-breaking heat wave in summer 2023 (Table 3).

PyPSA-USA uses the network representation built by Breakthrough Energy, including over 2240 buses in ERCOT, to simulate power transmission [65]. Here we clustered all buses and transmission lines using a k-means based clustering algorithm to partition the network into 10 zones (Fig. 2, right), following the methods of Hörsch and Brown [66].

Historical load data for 2020–2023 were taken from EIA-930 [67]. Given the significant load shedding that occurred during Uri, we replace load data during that period with ERCOT's estimate of what load would have been in the absence of load shedding ERCOT [63], although Lee and Dessler [2] estimate load would have been even higher. To account for load growth through 2030, we applied monthly multipliers to the historical load estimation. These multipliers were calculated by dividing the projected future monthly peak demand (forecast by ERCOT in 2023) by the historical peak demand for each month.

Capacity estimates from ReEDS for 2030 were assigned to the 10 zones based on their locations in the 2022 EIA plant database [46]. For plants projected to be constructed post-2022, the added capacity was allocated to the same zones as existing plants of each type, incorporating growth rates to reflect the capacity expansion from 2022 to 2030. In scenarios of new potential investments, the newly introduced capacity is assumed to be distributed evenly among existing plants within the zones of designated ReEDS balancing areas. For two energy efficiency scenarios, the monthly multipliers were scaled down based on the demand savings in our projection (see details in 3.4).

While minimizing the system cost, the model did not allow the addition or retirement of any plants but assigned a high expense to loss of load ($10,000/kWh) to prioritize mitigation of shortfalls, which would occur if resources could not meet demand at any time. At each hour, we applied historical outage rates from ERCOT [68] for each generator type to set the maximum available capacity in each hour. Wind and solar plants were also subjected to weather profiles extracted from the ERA5 time-series data [69]. We assumed a capacity factor of

Table 3
Extreme weather events in Texas, 2020–2023.

Event	Period	Significance
Winter storm Uri	Feb. 13–19, 2021	Coldest temperatures since 1989. Blackouts affected at least 10 million customers.
Winter storm Elliott	Dec. 21–26, 2022	Severe winter storm with conservation notices but no power shortfalls
Summer heat wave	June 1–Aug. 31, 2023	Second hottest summer on record by average temperature. Record electricity demand and several conservation requests but no load shed.

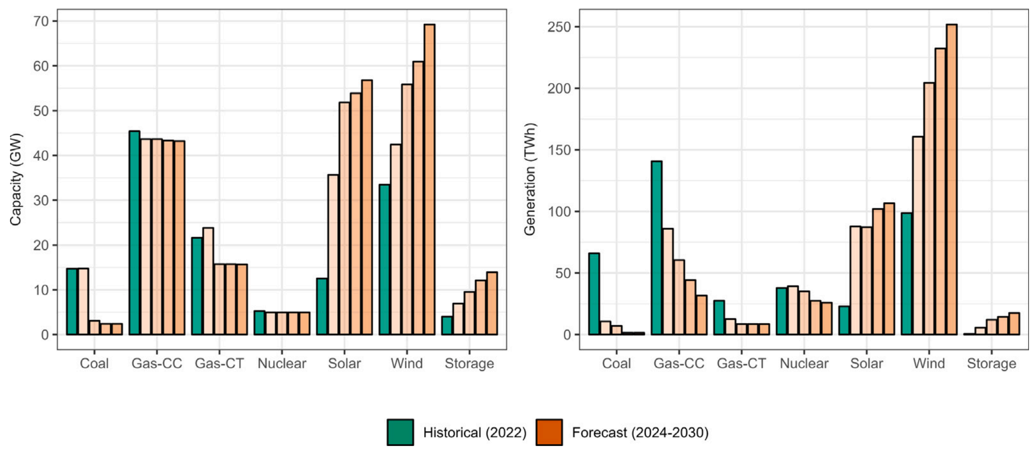

Fig. 3. Historical (2022) and forecast (2024–2030, in two-year increments) capacity (left) and generation (right) in ERCOT by plant types.

90% for any new geothermal plants based on the U.S. DOE GeoVision study DOE [70].

PyPSA-USA was used to assess grid resource adequacy by comparing a reference case with scenarios with additional generation resources or efficiency practices added. Since the model focuses solely on ERCOT, the interregional HVDC transmission scenarios were not included. To evaluate the value of bolstering transmission within ERCOT, we considered two scenarios: one maintaining the status quo and the other allowing expansion of transmission capacity between ERCOT zones.

Resource adequacy was quantified by calculating the aggregate shed load and the fraction of hours within each period that had load shed exceeding 0.1 GW. In this study, we defined those hours as "high-risk" in the absence of extraordinary measures to reduce load. Improvements were assessed by subtracting aggregate shed load in each scenario from the reference scenario.

3. Results

3.1. Reference scenario in 2030

We began by comparing historical capacity and generation data with the model forecasts under the reference scenario (Fig. 3). ReEDS projects solar and wind capacity to grow to 56.8 GW and 69.2 GW, respectively, by 2030 and grow more slowly afterwards. ReEDS anticipates retirements of 13.2 GW of coal and net retirements of 7.8 GW of Gas-CT by then. ReEDS projects that annual generation from solar and wind in 2030 will be 3.3 and 1.9 times, respectively, the 2022 levels in ERCOT. That would bring their combined share of generation to 83% in 2030, compared to 31% in 2022.

Fig. 4 compares generation by resource in 2020–2022 with ReEDS projections for 2030 on a time slice basis. Generation is projected to shift dramatically from gas and coal to solar and wind, particularly during spring and winter daytime periods. Solar is projected to provide the majority of power during daytime and wind the majority at night. Generation from natural gas and coal would occur mainly during summer and fall afternoons and evenings.

The shift from fossil fuels to solar and wind would slash greenhouse gas and air pollutant emissions in ERCOT (Fig. 5, top). CO_2,equivalent emissions would drop from 113 Mt in 2022 to 17 Mt in 2030, a 84% reduction. SO_2 and NO_x emissions would decline from 52.6 and 54.6 Ktons in 2022 (from ReEDS projection) to 4.0 and 9.8 Ktons in 2030. That would save 250 to 456 annual premature deaths caused by air pollution, according to the range of estimates from the three reduced-complexity models within ReEDS (Fig. 5, bottom).

The grid resource adequacy for 2030 was assessed using capacity projections from ReEDS and hourly weather data from 2020 to 2023, incorporating the anticipated monthly load growth. In the reference scenario, 31.7% of hours during winter storm Uri, 5.8% during winter storm Elliott, 6.2% during the 2023 heat wave, and 3.7% of hours in remaining hours are found to lack sufficient resources to satisfy projected demand. Allowing transmission expansion within ERCOT would reduce the percentages to 26.9%, 0%, 1.7%, and 2.2%, respectively.

The high outage rates projected for winter storm Uri arose in part from our assumption that future outage rates would match outage rates observed during the corresponding event. During Uri, all types of generation performed poorly, with median outage rates of 40% for Gas-CC, 46% for other gas plants, 29% for coal, 26% for nuclear, 14% for wind, and 34% for solar [71]. Winterization of power plants and gas supply systems in the aftermath of Uri aimed to reduce those outage rates [72].

We also assessed the average load shed during high-risk hours to characterize the need for additional generation capacity. If without transmission expansion, a repeat of Winter Storm Uri meteorology and outage rates together with reference case resources and demand projected to 2030 would lead to 31.7% of hours would have insufficient supply to match the projected demand; on average, 12.7 GW of demand during high-risk hours that could not be met, with peak load sheds over 30 GW (8–10 PM on February 15th). With transmission expansion, on the other hand, the fraction of high-risk hours would reduce to 26.9% while the average and peak sheds would remain high.

In contrast, during the milder conditions of winter storm Elliott, only 5.8% of hours would be considered the high-risk and the shortfall would average only 0.5 GW. Allowing transmission expansion, these high-risk hours would be fully eliminated. During the heat wave, 1.7% and 6.2% of hours would become high-risk with or without transmission expansion, with average shortfalls of 1.7 and 2.4 GW during the heat wave.

Fig. 6 illustrates how high-risk hours are distributed across different times of day during the three extreme events and the rest of hours.

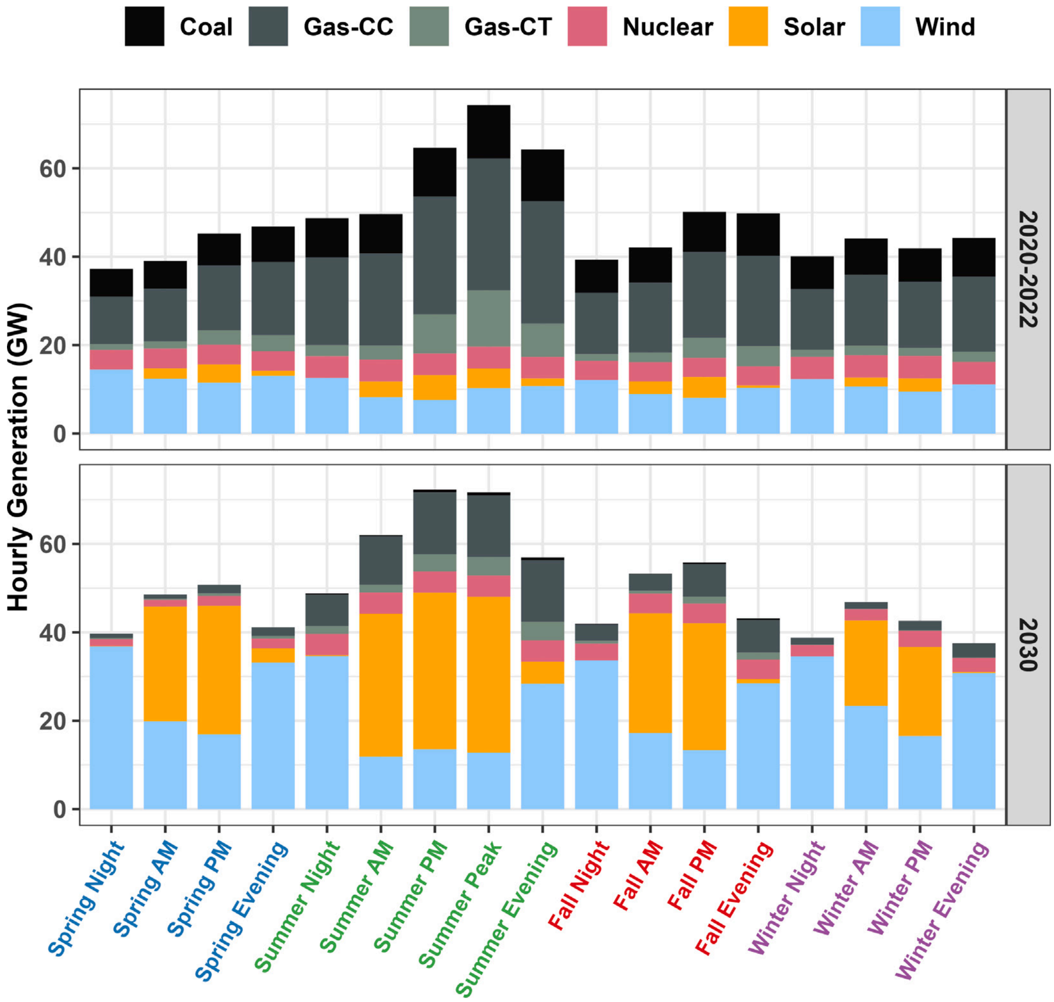

Fig. 4. The hourly dispatch in ERCOT by time slice (GW) in 2020–2022 (top) and the 2030 reference scenario (bottom).

For winter storms like Uri and Elliott, high-risk hours occur mainly after sunset and early in the morning due to elevated heating demand. Shortfalls projected for Uri range from 1.2 to 33.7 GW with an average of 12.6 GW. For Elliott, projected shortfalls peak at 0.8 GW. During heat waves, resource inadequacies are most likely to occur after sunset, when energy demand remains high while solar output vanishes; the maximum projected shortfall is 10.7 GW. The highest projected shortfall outside these events is 16 GW during a February 2023 winter storm, with demand reaching 81 GW and wind and solar generation falling to just 5 GW. The figure also shows that allowing transmission expansion within ERCOT sharply reduces the fraction of high-risk hours. The hourly dispatchable profile by generator types against the demand is plotted in Fig. D.1.

3.2. Scenarios: Adding dispatchable capacity or storage

We next examine the potential impacts of prescribing the additions of 10 GW of dispatchable capacity or storage in 2030. We analyze how these additions would affect capacity and generation from new and remaining resources and associated impacts on emissions and health. We focus on capacity and generation changes within ERCOT and emissions and health benefits across the continental U.S.

Table 4 presents the changes in capacity in 2030 compared to the reference scenario under each prescribed addition of resources. ReEDS projects that all remaining coal plants would be closed under all but one of the resource addition scenarios (*2* h *Bat*), as the additions would negate the need for coal generation.

Under prescribed additions of 10 GW Gas CC, Gas CT, or Geothermal, approximately 5 GW of vintage Gas-CT plants would retire and additions of battery storage and wind would slow (Table 4), as the new plants would reduce the needs for other resources. The 4- and 8-h battery scenarios would also allow some existing Gas-CT plants to close.

Additions of new capacity would mainly displace generation from coal plants and drive slight changes in output from wind and solar. On a time slice basis (Fig. 7), the gas addition scenarios mainly drive dispatch shifts during evenings and summer afternoons, when the new gas plants would mainly substitute for coal and vintage gas plants. The geothermal scenario reduces the use of all other resources, since geothermal would be dispatched ahead of fossil fuels because of low operations and maintenance (O&M) costs and even old wind and solar farms that do not receive production tax credits. Battery systems, particularly ones with 4-h and 8-h duration, would displace gas and coal use during afternoons and evenings and summertime peaks.

Adding 10 GW of Gas-CC or Gas-CT plants would increase $CO_{2,e}$ emissions by nearly 1.4 or 2.5 Mt, respectively, due to the higher utilization of gas plants (Fig. 8). Conversely, adding 10 GW of geothermal plants would reduce $CO_{2,e}$ emissions by 6.7 Mt annually. Adding battery systems of 2-, 4-, or 8-h duration would result in $CO_{2,e}$ reductions of 2.1, 3.0, or 4.5 Mt, respectively.

All of the scenarios yield reductions in SO_2 emissions by reducing the use of coal, the dominant source of power plant SO_2. ReEDS projects that either of the Gas scenarios would reduce SO_2 emissions by more than 3 Kt (Fig. 8 bars). NO_x impacts are more variable, since NO_x is emitted by both coal and gas plants, with Gas-CT emitting

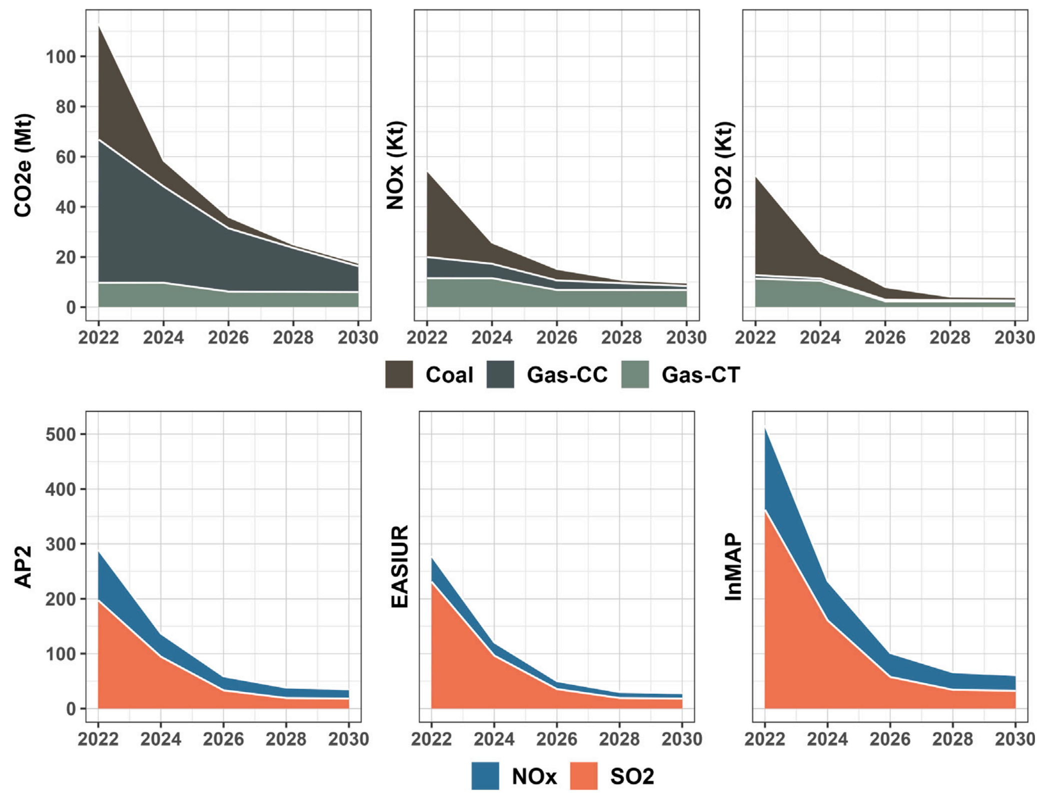

Fig. 5. Annual emissions in ERCOT and associated air pollution-caused mortality predicted by three reduced-complexity models in ReEDS.

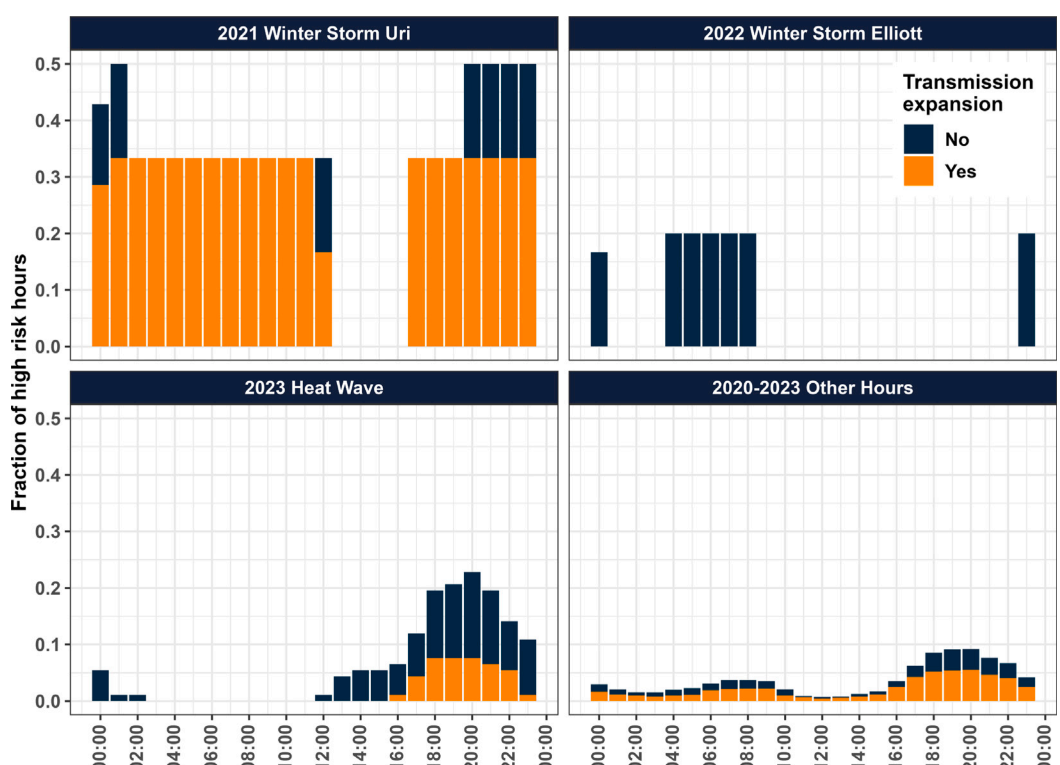

Fig. 6. Fraction of high-risk hours by hour of day within three extreme weather periods and all other hours under 2020–2023 meteorological conditions and 2030 reference scenario projected capacity and demand in ReEDS, depending on whether the model allows transmission expansion within ERCOT (orange) or not (blue).

Table 4
Capacity changes in ERCOT in 2030 after adding 10 GW of dispatchable capacity or battery storage. REF indicates the original capacity reported in the reference scenario. Net change (GW) and relative change (%) are shown in (X | Y%) format.

Tech	REF	Gas CC	Gas CT	Geo	2 h Bat	4 h Bat	8 h Bat
Coal	2.4	−2.4 | −100%	−2.4 | −100%	−2.4 | −100%	−1 | −40%	−2.4 | −100%	−2.4 | −100%
Gas-CC	43.2	10 | 23%	0 | 0%	0 | 0%	0 | 0%	0 | 0%	0 | 0%
Gas-CT	15.7	−4.5 | −29%	5.4 | 35%	−4.5 | −29%	0.1 | 1%	−1.3 | −8%	−4.7 | −30%
Nuclear	5	0 | 0%	0 | 0%	0 | 0%	0 | 0%	0 | 0%	0 | 0%
Storage	14	−2.6 | −19%	−2.6 | −18%	−1.4 | −10%	6.7 | 48%	6.6 | 47%	7.3 | 52%
UPV	56.8	0.5 | 1%	0.8 | 1%	4.3 | 8%	−0.2 | 0%	−0.2 | 0%	−0.2 | 0%
Wind	69.2	−3.8 | −5%	−3.3 | −5%	−12.7 | −18%	0 | 0%	2.2 | 3%	2.4 | 3%

Table 5
Capacity and generation changes in ERCOT and CONUS after building new transmission capacity in 2030.

Region	Fuel	Capacity changes (GW | %)			Generation changes (TWh | %)		
		Trans East	*Trans West*	*Trans Both*	*Trans East*	*Trans West*	*Trans Both*
ERCOT	Coal	0 | 0%	0 | 0%	0 | 0%	0 | 0%	0 | 0%	0 | 0%
	Gas-CC	0 | 0%	0 | 0%	0 | 0%	−3.7 | −10%	2.7 | 7%	−1.5 | −4%
	Gas-CT	0 | 0%	0 | 0%	0 | 0%	0 | 0%	0 | 0%	0 | 0%
	Nuclear	0 | 0%	0 | 0%	0 | 0%	−0.6 | −2%	0.9 | 3%	1.3 | 4%
	UPV	0 | 0%	0 | 0%	0 | 0%	−1.4 | −1%	−1.4 | −1%	−3.4 | −3%
	Wind	6.2 | 10%	3.2 | 5%	9 | 15%	25.1 | 11%	12.9 | 6%	36.4 | 16%
CONUS	Coal	0.4 | 0%	0 | 0%	0.2 | 0%	−1.9 | −2%	−5.8 | −6%	−7 | −7%
	Gas-CC	0 | 0%	0 | 0%	0 | 0%	−9.3 | −1%	1 | 0%	−2.4 | 0%
	Gas-CT	−0.3 | 0%	0 | 0%	0 | 0%	−0.2 | 0%	0 | 0%	0 | 0%
	Nuclear	0 | 0%	0 | 0%	0 | 0%	−0.7 | 0%	0.3 | 0%	−0.2 | 0%
	UPV	−3.2 | −1%	−0.4 | 0%	−3.5 | −1%	−10.8 | −1%	−1.4 | 0%	−8.8 | −1%
	Wind	5.7 | 2%	1.5 | 0%	4.6 | 1%	24.9 | 2%	5.9 | 0%	18.5 | 1%

more than Gas-CC per unit of electricity. Translating the SO_2 and NO_x emission changes to health impacts using the three reduced-complexity air quality models in ReEDS indicates that *Gas CC* would avoid an average of 21 premature deaths annually, while *Gas CT* would avert 13 deaths (Fig. 8 line).

If it becomes feasible to add 10 GW of geothermal plants, the emission reductions and health benefits would be much larger (Fig. 8). The battery scenarios also yield reductions in emissions and associated mortality.

3.3. Scenarios: Adding HVDC transmission

ReEDS does not expect additions of transmission interconnections to change coal or gas capacity in either ERCOT or other U.S. grids. Instead, it would spur development of wind and solar farms, with much of the associated generation exported to neighboring grids or displacing gas and nuclear use in both ERCOT and neighboring grids.

Table 5 presents ReEDS projections on the impact of the transmission addition scenarios on capacity and generation for ERCOT and the U.S. Adding HVDC transmission to connect ERCOT to the Eastern Interconnection (*Trans East*) would spur the construction of 3.9 GW more wind capacity in ERCOT, and the (*Trans West*) scenario would add 3.8 GW more wind. The combined effect of both transmission additions (*Trans Both*) would be slightly less than additive. Changes outside ERCOT would be slight, although some of the wind gains in ERCOT are offset by reductions in other states. The net increases in wind would lead to less dispatch of gas in the Trans East scenario and less dispatch of coal in the Trans West scenario, and of both in the combined scenario.

By enabling more wind and solar to displace fossil fuels within and beyond ERCOT, building new transmission to the East and/or West interconnections would reduce $CO_{2,e}$, SO_2, and NO_x emissions and associated air pollution related mortality by the amounts shown in Fig. 8. Most of the displacement of fossil fuels, and thus most of the emissions reductions and health benefits, would occur outside ERCOT (Table 5).

3.4. Scenarios: Improving energy efficiency

We investigated the potential impacts of updated energy efficiency practices in the residential, commercial, and industrial sectors. By 2030, the *EE MOD* and *EE AGG* scenarios could enable ERCOT to reduce electricity use by up to 5.1% and 9.9%, respectively, during summer peak hours. Reductions range from 1.1–6.2% for *EE MOD* and 2.1–12.0% for *EE AGG* across different regions and time slices, with seasonal averages shown in Fig. 9 (left). The largest demand reductions occur on summer afternoons and evenings, as the potential to increase the energy efficiency of cooling is large. Fig. 9 (right) shows load reductions by sector. We find greater opportunities for demand reduction in the residential sector than in the commercial and industrial sectors.

Reduced loads in ERCOT would slightly reduce the need for existing dispatchable resources, such as coal and vintage gas plants, while ensuring peak demand is met. In terms of annual generation, 1.2 TWh less fossil-fuel gas would be dispatched under the *EE MOD* scenario, and 2.1 TWh less under the *EE AGG* scenario. However, due to the overall load reductions throughout the year, 3.1 GW and 5.7 GW of wind plants would not be built under the *EE MOD* and *EE AGG* scenarios, respectively.

As a result, *EE MOD* would reduce 1.7 Kt of SO_2, 1.1 Kt of NO_x, and 0.9 Mt of $CO_{2,e}$, potentially preventing 55 deaths due to improved air quality. Although load reduction is nearly twice as large under *EE AGG*, the benefits would be less than double because fewer wind plants would be built.

3.5. Impacts on resource adequacy

Fig. 10 displays enhancements in resource adequacy resulting from each infrastructure addition. For winter storm Uri, new investment scenarios exhibited varying degrees of improvement in resource adequacy, from no effect up to 26% fewer high-risk hours than the reference scenario. For the less severe Elliott, any of the new investment scenarios would be sufficient to eliminate high-risk hours altogether. During heat waves, the intra-ERCOT transmission system would play a pivotal role to enhance adequacy. Future wind, solar, and storage capacities will

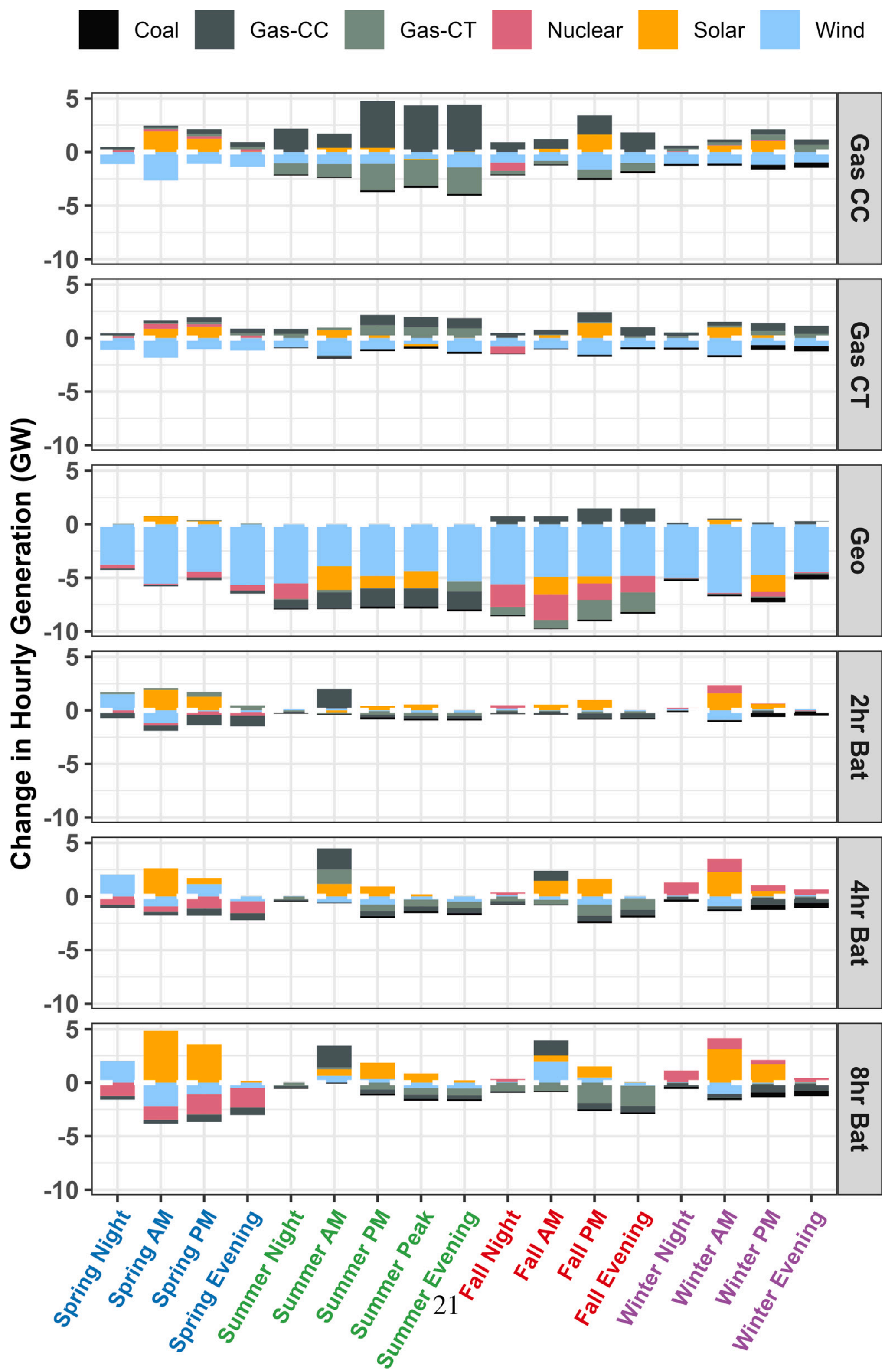

Fig. 7. Dispatch changes by time slice upon prescribed capacity additions in 2030.

all necessitate additional transmission capacity to efficiently transmit clean energy to load centers.

Scenarios adding dispatchable generation (*Gas CC*, *Gas CT*, and *Geo*) would significantly reduce the number of high-risk hours in all events, but still leave 7.4–10.8 GW of shortfalls during Uri. Apart from Uri, most of the shortfalls that would remain under each of the dispatchable plant addition scenarios would have magnitudes of only about 1 GW. Short-duration battery systems would offer only moderate enhancements to resource adequacy during winter storms, when demand peaks amid dark conditions. Batteries are more effective in averting high-risk hours as the sun sets during heat waves.

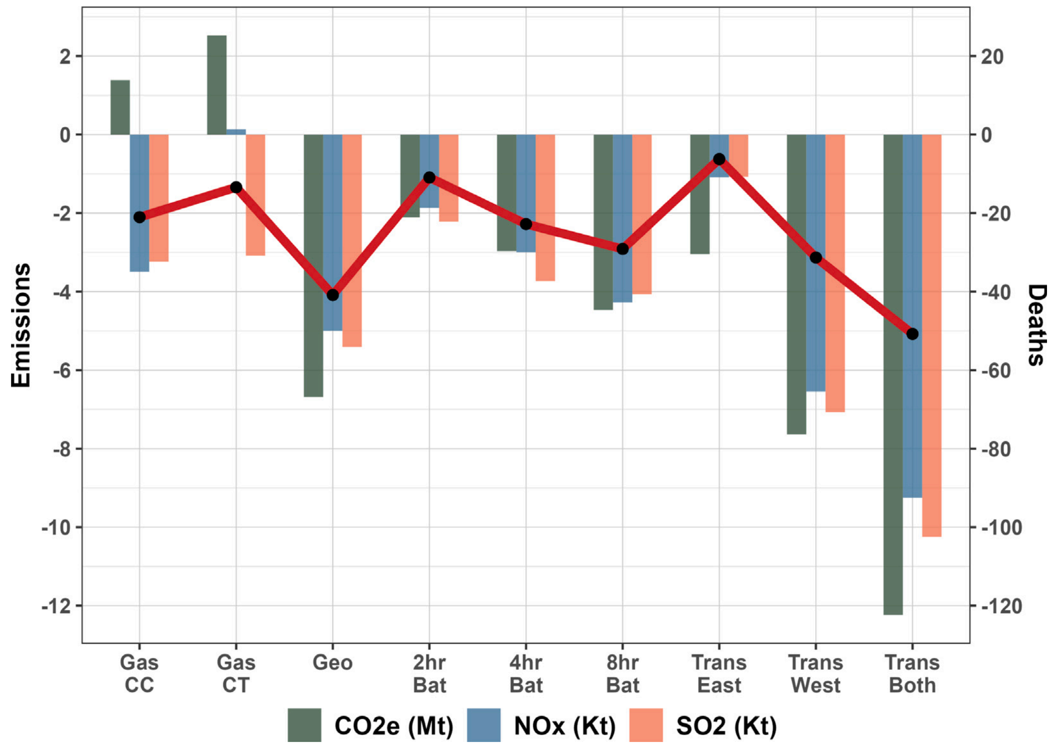

Fig. 8. The emission and mortality changes under each scenario relative to the base case in 2030. Bars show changes in emissions and the line shows changes in air pollution related mortality.

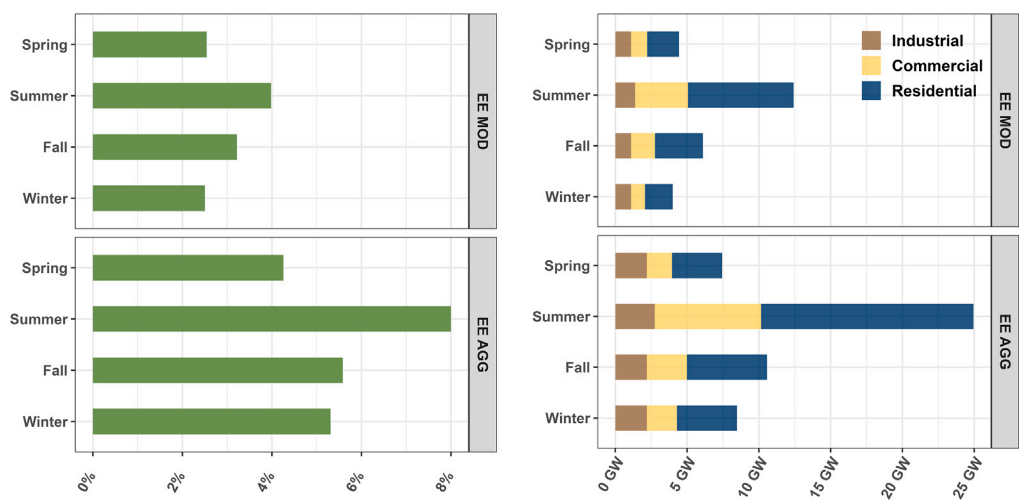

Fig. 9. Left: Percentage of total load reduction aggregated by season from two energy efficiency scenarios. **Right:** GW of load reduction from the industrial, commercial and residential sectors.

4. Discussion

Our findings indicate that additions of dispatchable capacity, whether gas or geothermal, would tend to accelerate the retirements of coal plants in ERCOT while only slightly slowing wind and solar growth, thus reducing the emissions and health impacts of power plants overall. Further work is needed to assess the feasibility of the geothermal scenario [73,74]. Additions of 4- or 8-h battery systems would also accelerate coal retirements, but 2-h systems would have less effect. Enhancements to transmission capacity within ERCOT will be needed to fully realize the benefits of any investments that are not sited in high-load regions.

Modeled capacity factors of coal, Gas-CC, and Gas-CT plants in ERCOT average only 6, 19, and 13% in 2030 in the reference case, and are similarly low in the other scenarios. That is far lower than their average capacity factors in 2020–2022 (coal at 54%, Gas-CC at 43%, and Gas-CT at 15%). Although other studies also project low capacity factors for thermal plants (e.g., Deetjen et al. [30]), it is questionable whether power plant operators would find it profitable to continue operating plants at such low capacity factors.

The HVDC transmission scenarios considered here also yield sizeable reductions in emissions, mostly by enabling more wind farms to displace fossil fuels within and beyond ERCOT. This is consistent with other studies that found that transmission lines can be crucial for renewable energy development and decarbonization [75–78].

Improving energy efficiency would also greatly reduce annual dispatch from fossil-fueled plants. While the model minimizes costs system-wide, it omits additional benefits of energy efficiency, such

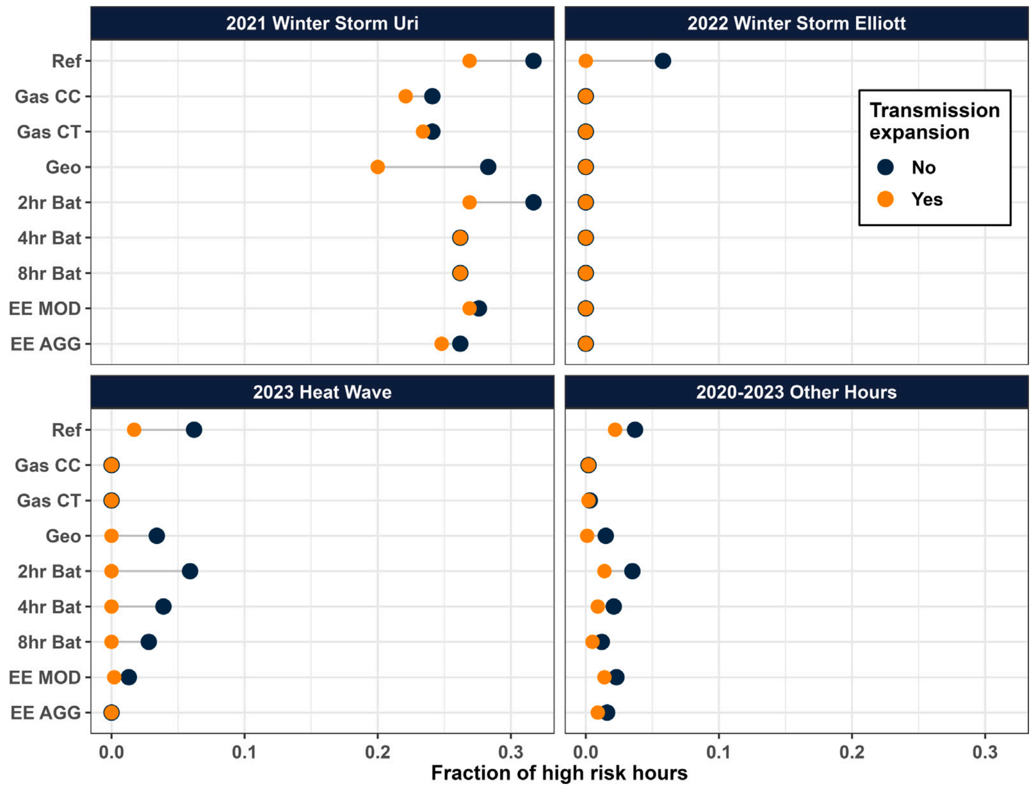

Fig. 10. The fractions of high-risk hours under the reference scenario (first row) and scenarios involving resource additions. The orange and blue endpoints indicate scenarios with and without allowing transmission expansion within ERCOT.

as utility bill savings and improved resilience against energy price volatility.

This study demonstrates that capacity expansion models such as ReEDS can be valuable tools for projecting the expansion of electric power capacity and generation while assessing environmental impacts. When coupled with short-term operational tools such as PyPSA-USA, the integrated model can provide a more comprehensive understanding of grid operations during peak demand periods. This approach allows for a detailed analysis of how future grid capacities can be optimized to handle high-demand scenarios effectively.

Our analysis used a one-way modeling approach, using PyPSA-USA to evaluate resource adequacy based on capacity expansion results from ReEDS. An alternative would be an iterative framework that couples capacity expansion with production cost, resource adequacy, or power flow models, enabling feedback between planning and operations [79, 80]. In such frameworks, system reliability is assessed at each iteration, and investment decisions are updated if adequacy criteria are not met. While this could improve planning robustness, fully coupling models increases computational complexity. Without full integration, feedback from PyPSA-USA would likely have limited impact on ReEDS outcomes.

However, it is important to exercise caution when interpreting the results. Capacity expansion models rely on simplified assumptions regarding the behavior of electricity markets and the technical characteristics of power generation technologies. Additionally, since the demand was externally defined, we did not consider its potential response to the various scenarios. Future electricity demand is highly uncertain due to several emerging trends, including rapid growth of energy-intensive data centers, increased electrification of transportation and heating systems, and the expanding role of distributed resources such as microgrids. These developments could significantly reshape load profiles and total demand, thereby influencing investment and operational decisions in ways not captured in this analysis.

The scenarios examined in this study were formulated based on existing policy, without constraining the model to achieve U.S. commitments under the Paris climate agreement. Future work could examine how climate policy and electrification would affect the impacts of capacity and transmission expansion scenarios. Additionally, multi-resource interactions, such as the simultaneous expansion of renewable energy, storage, and transmission infrastructure, could lead to different dynamics in resource allocation and system optimization, which should be considered in future studies. Incorporating extreme weather conditions more explicitly into long-term planning models could also enable capacity planning to better account for climate-related reliability risks. Such integration would enable a more direct link between observed risk hours and the scale of additional investments needed to maintain reliability under increasingly volatile conditions.

While this study focuses on the technical feasibility of various capacity expansion and transmission scenarios, real-world implementation is shaped by a broader set of constraints that extend beyond engineering considerations. Political resistance, permitting delays, and public opposition that involve intense disturbance of land use can slow or halt deployment. The capital-intensive nature of dispatchable generation and long-distance transmission further poses financing challenges, particularly in the absence of stable long-term policy support. Moreover, shifting federal and state policies, volatile fossil fuel prices, and evolving clean energy tax incentives introduce substantial uncertainty into investment decisions and system planning. Energy system models typically assume stable policy environments or predefined scenarios; however, real-world policies often change in response to political, economic, or social factors, potentially altering carbon pricing, renewable incentives, or fossil fuel subsidies. These uncertainties, along with regulatory hurdles and stakeholder preferences, underscore the need for future work to integrate policy dynamics, economic barriers, and societal perspectives to better evaluate the feasibility and broader implications of grid transformation strategies.

5. Conclusion

We used a long-term capacity expansion model coupled with a short-term power grid operational model to simulate the potential emissions and resource adequacy impacts of hypothetical additions of generation, storage, and transmission resources and energy efficiency improvements in Texas' ERCOT electricity grid. Our coupling of the two models enabled us to jointly consider long-term capacity growth and short-term grid operation, incorporating historical weather conditions, plant outages, and demand. However, the models rely on simplified assumptions about electricity market behavior and power generation technologies and treat demand exogenously. The simulations were motivated by state legislation in 2023 that incentivized new dispatchable power plants (Senate Bill 2627), clarified the regulation of geothermal energy (Senate Bill 785), and incentivized the construction of transmission lines (House Bill 1500), although actual additions of resources will differ from the scenarios modeled here.

Our modeling shows that, so long as they are not accompanied by impediments to renewable energy, investments in dispatchable capacity, battery storage, and energy efficiency would each accelerate the retirement of coal plants but only slightly slow the growth of wind and solar capacity, leading to net reductions in emissions. Each of these investments would also improve resource adequacy during periods of high demand or extreme weather in Texas, including heat waves and winter storms. Even greater emissions reductions and health benefits could be achieved through enhanced geothermal systems, long-duration battery storage, and high-voltage transmission interconnections, but each of those is for now far costlier and more challenging to construct than the other options.

Our findings may alleviate concerns that investments in natural gas plants would worsen emissions, so long as they are driven by policies that incentivize dispatchable generation rather than penalize variable renewable generation. Wind and solar farms have near-zero marginal costs, so they will continue to deploy as much as wind and solar conditions allow, within the constraints of transmission. New gas plants would compete mainly with existing gas and coal plants and operate at low capacity factors as wind, solar, and batteries continue to proliferate. Thus, incentivized gas plants are more likely to become poor investments and stranded assets that squander state resources rather than net contributors to emissions.

CRediT authorship contribution statement

Chen Chen: Conceptualization, Investigation, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Validation. **Caroline M. Hashimoto:** Investigation, Software, Data curation, Writing – review & editing. **Daniel S. Cohan:** Conceptualization, Funding acquisition, Investigation, Project administration, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Data and models

See Tables A.1 and A.2.

Appendix B. Historical and future ERCOT grid spare reserve

Texas has the second-largest population and the highest energy consumption among all U.S. states [67]. Despite the rapid growth of wind and solar capacity in the last couple of years, Texas still heavily relies on fossil fuels, which makes it the highest power sector SO_2 and NO_x emissions across all states [14]. It operates as an isolated system and has limited transmission interconnection to other interconnections. By the end of 2022, Texas has 23 coal fleet, 182 combined-cycle gas units, 188 combustion-turbine gas units, 4 nuclear units, 150 solar farms, 329 wind farms, and a variety of other types of plants, which offers a total of 380 GW of nameplate capacity but only 77 GW are dispatchable. In this Appendix, we estimated the historical dispatchable reserve based on the hourly data mainly acquired from ERCOT and EIA. In addition, we forecasted the scarcity in power supply that is likely to occur in ERCOT if demand grows without substantial additions of dispatchable resources.

Fig. B.1 illustrates the process that we found the grid vulnerable hours in 2020 to 2022. We computed these metrics for each hour of 2020–2022 using the following data from ERCOT and the Energy Information Administration (EIA): historical load from ERCOT Hourly Load Data Archives; 15 min generation from ERCOT Fuel Mix Reports; monthly capacity for non-intermittent renewable resources from EIA Form EIA-860M; monthly capacity for intermittent renewable resources (IRR; i.e., wind and solar) from ERCOT Resource Capacity Trend Charts; and outage data from ERCOT Hourly Resource Outage Capacity Reports and Unplanned Resource Outages Reports.

The historical ERCOT load data, covering eight weather zones from 2020 to 2022, were compared against generation profiles aggregated from 15 min intervals (Fig. B.2), which showed discrepancies between hourly load and generation. We used K-means clustering to categorize hours into three distinct groups based on their time and seasonal characteristics. Adjustments were made to the generation data using linear regression models for each cluster, with differences allocated among gas combustion turbines, combined-cycle gas, and coal generation. During Winter Storm Uri, the actual demand was underestimated due to load shedding, thus we replaced the historical loads with the ERCOT's estimated non-shed load for February 15–19th, 2021, for accuracy in analysis.

On the supply side, we tabulated the Preliminary Monthly Electric Generator Inventory from EIA to nameplate capacity by plant type and month. The operating generator table includes all operating units to the version release date (December 2022), and the retired capacities were added back to months before those fleets were retired. For wind and solar capacity, we adopted the monthly capacity from Resource Capacity Trend Charts. In summary, the nameplate capacity is comprised of two data sources abovementioned, under monthly by coal, Gas-CC, Gas-CT, nuclear, solar, wind, and others. We then applied the start of month capacity to all hours within the month.

Since 2013, ERCOT has reported Hourly Resource Outage Capacity for various zones, detailing outages for thermal generators, intermittent renewable resources (IRR), and newly installed equipment not yet synchronized with the grid. This data set also includes seasonal outages and de-rates. For the duration of winter storm Uri, we replaced the data with the ERCOT estimated generator outages by cause updated report [4]. All outage data was consolidated to estimate fuel-specific hourly outages and calculate available capacity for all hours from 2020 to 2022.

We define parameters to represent conditions in ERCOT during each hour. Net load, defined as the difference between gross load and the generation provided by wind and solar (Eq. (B.1)), provides a measure of the burden on dispatchable resources. Available dispatchable capacity tallies the nameplate capacity of dispatchable resources (reported each month, m, for each unit, n) that is not experiencing an outage in hour h (Eq. (B.2)). The difference between these two terms, which we

Table A.1
Comparison of ReEDS and PyPSA-USA Models.

Model feature	ReEDS (Regional Energy Deployment System)	PyPSA-USA (Python for Power System Analysis - USA)
Developer	NREL (National Renewable Energy Laboratory)	Open-source community (based on PyPSA framework)
Primary Purpose	Long-term capacity expansion modeling	Power flow, resource adequacy, and operational analysis
Modeling Focus	Investment and policy scenarios over decades	Detailed operational behavior and grid constraints
Time Resolution	Representative time slices (e.g., 17 per year)	Hourly (8760 h/year)
Spatial Resolution	134 Balancing Areas in the U.S. (7 zones in ERCOT)	Customizable clusters (e.g., 10 zones in ERCOT)
Temporal Scope	2020–2050 (long-term planning)	Single or multi-year operations
Transmission Modeling	Zonal approximation of interregional flows	Nodal power flow with line constraints
Optimization Objective	Minimize system cost over multi-decade horizon	Minimize dispatch/operation cost within fixed capacities

Table A.2
Key data sources used in this study.

Data source	Description
Annual Energy Outlook (AEO; 2022)	Provides national and regional electricity demand projections used as load inputs in ReEDS [46].
Annual Technology Baseline (ATB; 2023)	The NREL Annual Technology Baseline offers projections of technology cost and performance for generation and storage resources [47].
ERCOT Monthly Outlook for Resource Adequacy (MORA; May 2024)	Generator build and retirement profiles from ERCOT's Monthly Outlook for Resource Adequacy for historical and projected generation [23].
ERCOT Generator Interconnection Status (GIS; Dec 2022)	Generator Interconnection Status Report provides detailed project-level data on future planned renewable and storage capacity additions [49].
Texas Commission on Environmental Quality (TCEQ) Emission Inventory (2021)	State-reported emissions data for estimating criteria pollutant rates from fossil fuel plants in ERCOT.

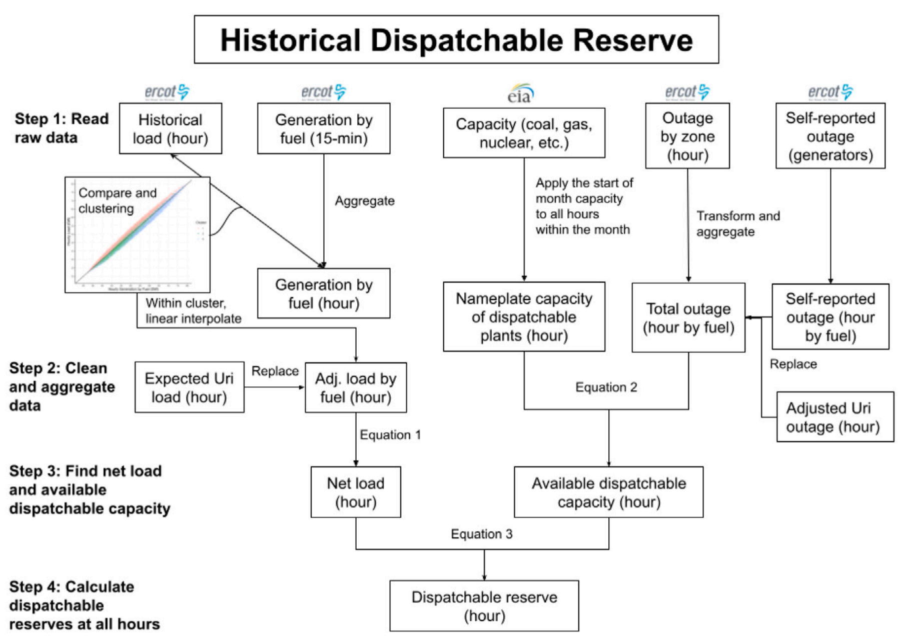

Fig. B.1. Flow chart of our methods for computing dispatchable reserve.

refer to as the dispatchable reserve (Eq. (B.3)), provides a measure of the spare capacity of dispatchable resources during each hour.

$$Net\ load\ (h) = Gross\ load\ (h) - Wind\ \&\ Solar\ generation\ (h) \tag{B.1}$$

$$Available\ dispatchable\ capacity\ (h) = \sum_{n=1}^{N} Nameplate\ capacity\ of\ dispatchable\ plants(n,m) - \sum_{n=1}^{N} Outages\ (n,h) \tag{B.2}$$

$$Dispatchable\ reserve\ (h) = Available\ dispatchable\ capacity\ (h) - Net\ load\ (h) \tag{B.3}$$

Using the results calculated, we simulated the grid conditions during Winter Storm Uri. On February 15th, thermal generator outages escalated due to inadequate weatherization, peaking over 30 GW for three days. Concurrently, both wind and solar generation was low, with a peak demand of 76.8 GW at 9 AM on February 16th while wind and solar managed only 5 GW. The net load reached 71.7 GW, but the available thermal capacity was limited to 47.7 GW, resulting in a shortfall of approximately 24 GW. These findings align closely with other studies [8,63,71] (see Fig. B.3).

We assessed energy scarcity in ERCOT by analyzing the average and minimum dispatchable reserves across each hour and month of

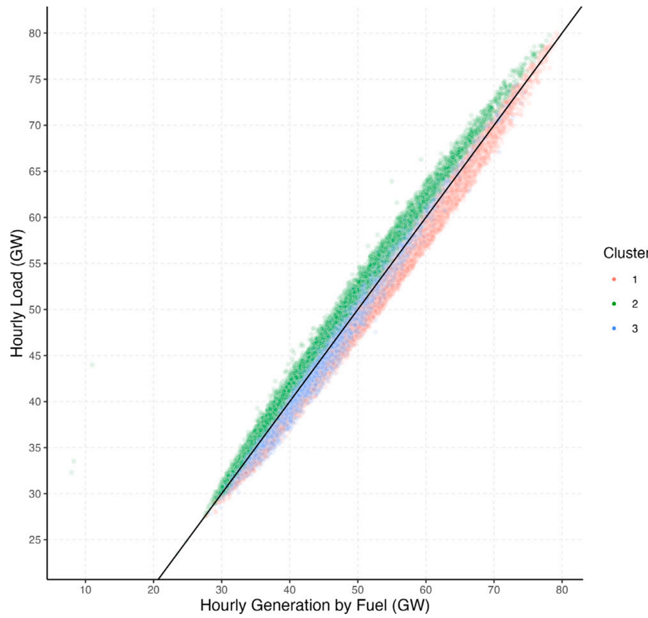

Fig. B.2. K-means clustering that clusters the historical load and historical generation by fuel into three groups.

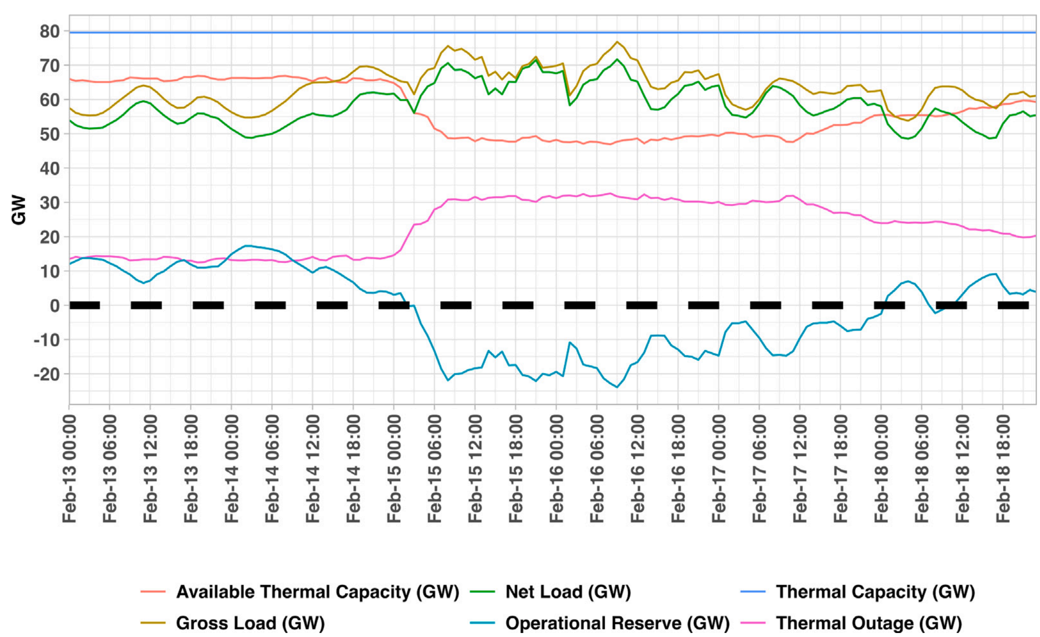

Fig. B.3. Simulated grid conditions during winter storm Uri.

2020–2022 (Figs. B.4 and B.5). Mean values were lowest during summer afternoons and evenings in all years, and during portions of spring and fall in 2020 and 2021 when maintenance outages at thermal power plants were most prevalent (Fig. B.4). The minimum dispatchable reserves represented the lowest reserves observed for each hour and month combination, highlighting the most vulnerable periods (Fig. B.5). Tightest conditions occurred during three types of periods: (1) summer afternoons and evenings, when hot temperatures drive up air conditioning demand; (2) winter storms in February 2021 and December 2022, which drove up heating demand and, especially in the 2021 freeze, generation outages; and (3) springtime maintenance of power plants.

We also performed an energy scarcity analysis based on the forecast load and model-predicted capacity in 2030. To account for spare reserve towards the future, we forecast gross load in 2030 by scaling up gross load from each hour in three historical weather years (2020, 2021, 2022) by the respective growth rates reported in ERCOT's 2023 Long-Term Load Forecast Report [22]. We then forecast net load for each hour in 2030 for those three weather years (Eq. (B.1)) by subtracting projected wind and solar generation, estimated by multiplying the modeled wind and solar capacities in 2030 with their historical capacity factors. We then calculated the average projected net loads for 2030 based on the three-year weather conditions.

We then used Eq. (B.2) to determine available dispatchable capacity. The 2030 nameplate capacity of each power plant was taken from the ReEDS projected reference case. We assumed that outage rates of each dispatchable resource type (coal, gas, and nuclear) in 2030 align with the average percentages observed in the corresponding hours of the base years in the ERCOT outage reports. Finally, we forecast the dispatchable reserve in 2030 by subtracting forecast net load from

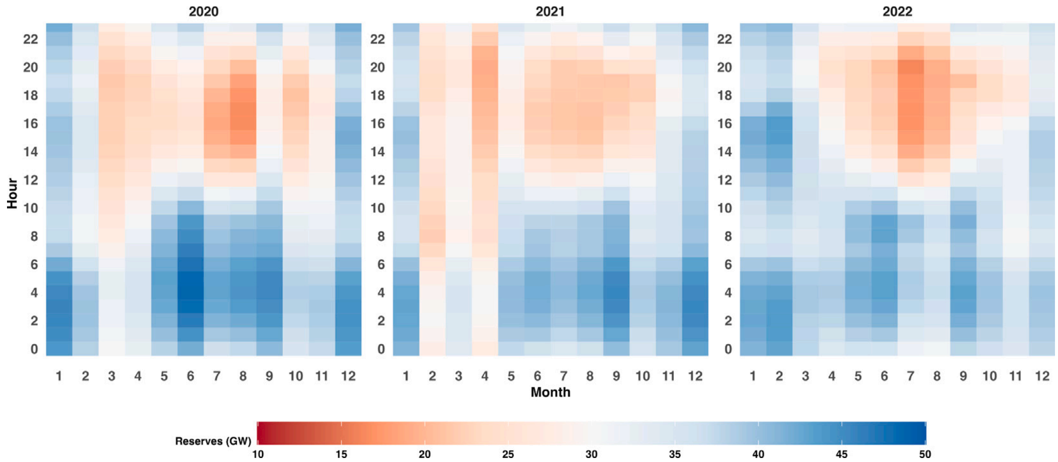

Fig. B.4. The average dispatchable reserve (GW) for each hour and month from 2020 to 2022.

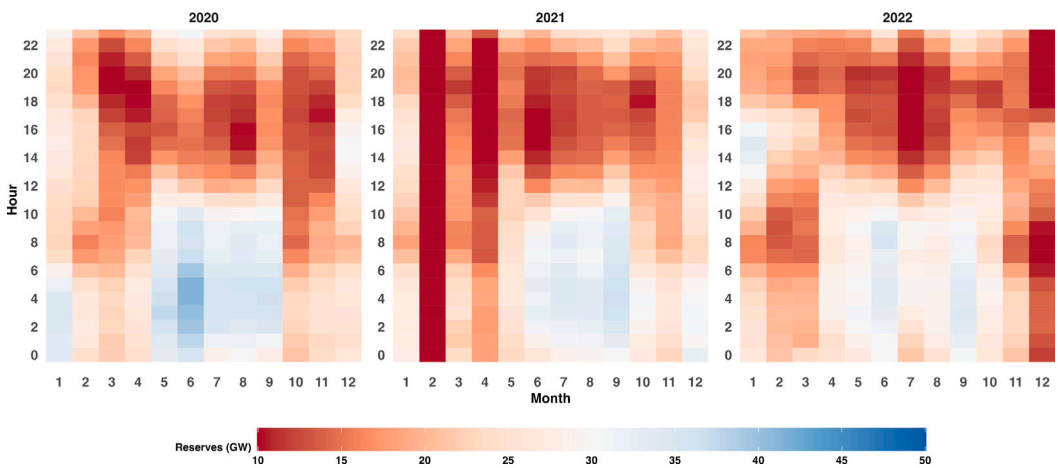

Fig. B.5. The minimum dispatchable reserve (GW) for each hour and month from 2020 to 2022.

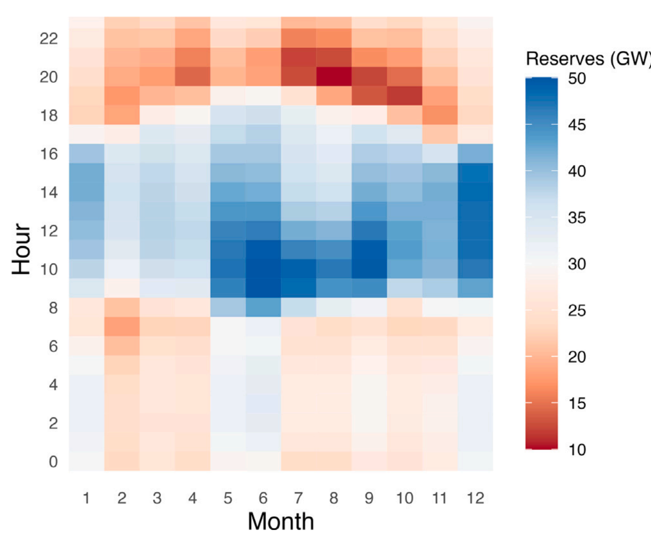

Fig. B.6. The mean dispatchable reserve (GW) combined by hour and month in 2030 based on the ReEDS' capacity and projected load in ERCOT.

forecast available dispatchable capacity (Eq. (B.3)). We binned results by month and time of day to identify when dispatchable reserves were most scarce.

Fig. B.6 presents the mean dispatchable reserve projected during each month and hour. In the default scenario, large solar output provides ample capacity throughout most daylight hours. However, with solar unavailable after sunset, reserves would become scarce on some evenings due to demand growth and power plant retirements. Compared to recent years shown in Figure A4, more hours have low

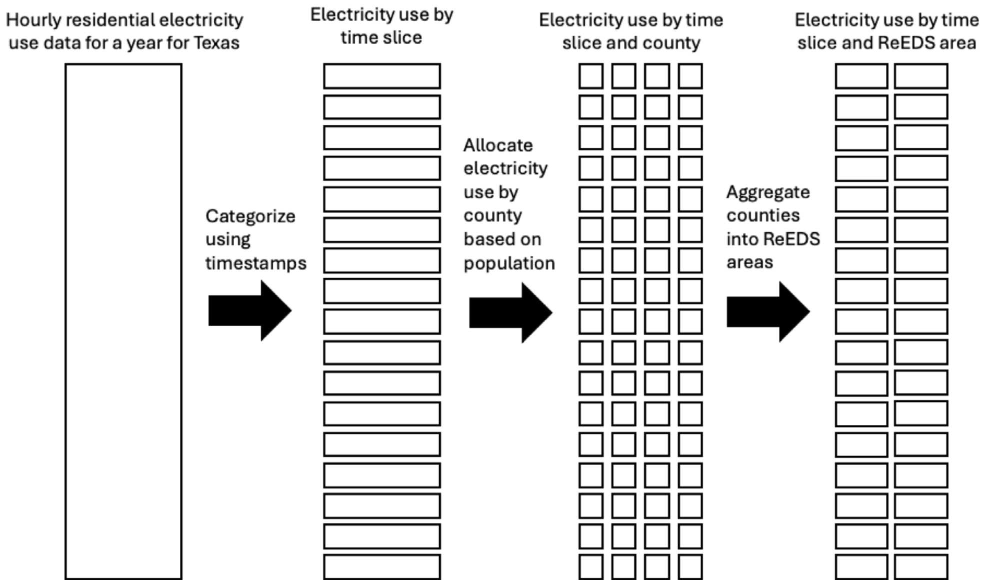

Fig. C.1. Flowchart of methods for disaggregating state-level industrial energy efficiency to ReEDS inputs.

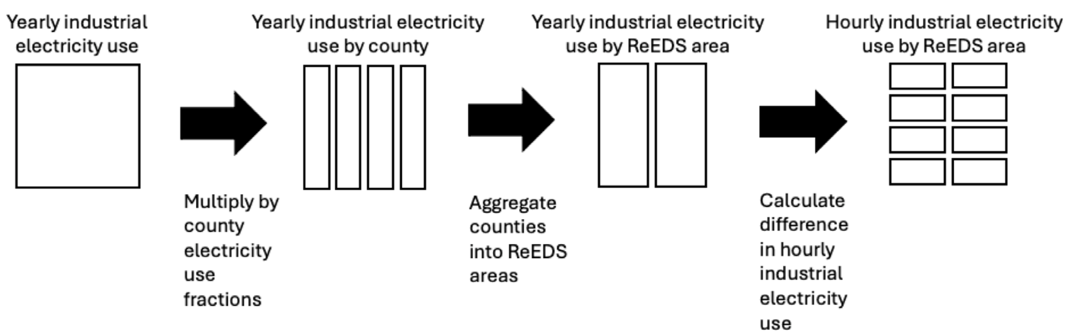

Fig. C.2. Flowchart to disaggregate state-level industrial energy efficiency to ReEDS inputs.

dispatchable reserves (< 10 GW) that could make them vulnerable to sudden spikes in demand or power plant outages.

Appendix C. Energy efficiency in texas

Data were imported from a year of hourly electricity use modeling from White et al. [21], which provides hourly electricity usage under standard, high efficiency, and ultra-high efficiency residential heating and cooling scenarios. Additionally, the data breakdown includes specific electrical consumption by central heating, central cooling, heating and cooling fans, and both regular and central system heat pumps. Energy savings for the moderate and aggressive scenarios were determined by calculating the difference between the standard and high efficiency scenarios, as well as between the standard and ultra-high efficiency scenarios.

Following the temporal resolution used in ReEDS, we categorized each hour into 16 different time slices to represent various parts of the day — overnight, morning, afternoon, and evening — across each season. Additionally, we identified the top 40 h from summer afternoon to represent the time slice with the peak demands, time slice 17. To distribute state-level energy savings to the ReEDS regions, we proportionally allocated the state's energy savings down to each county based on the county population. Finally, the county-level energy savings were aggregated into the larger ReEDS areas.

We assumed the impact of energy efficiency measures in the commercial building stock is roughly half as much of a change as to the residential sector based on Rhodes et al. [60] (see Figs. C.1 and C.2).

The assumptions to compile the industrial energy efficiency scenarios stem from the U.S. Energy Policy Simulator (EPS)'s Nationally Determined Contributions (NDC) scenario to align with the United States' commitments under the Paris Agreement Orvis and Mahajan [61]. In our methodology, we considered the percentage reduction in the NDC for the aggressive case, while halving this percentage reduction for the moderate case. To compute the actual electricity savings from these scenarios, we integrated a 7% improvement in industry energy efficiency by 2050 for the moderate case and a 14% improvement by 2050 for the aggressive case in the EPS tool. The tool endogenously estimates the electricity consumption from 2020 to 2050 leveraging parameters adjusted within the model.

Also drawn from the NDC scenario, enhanced material efficiency, longevity, and re-use policies projected for 2050 would result in a 5% additional decrease in cement demand and a 7% reduction in iron and steel demand by 2050 under the moderate case. In the aggressive case, these policies would yield a more pronounced effect, with a 10% reduction in cement demand and a 15% reduction in iron and steel demand by 2050.

County-level industry data were used to estimate reductions in each county's industrial electricity use for the moderate and aggressive scenarios [62]. A spreadsheet containing information on county-level resource usage for various industries labeled by NAICS code was used to calculate total industrial electricity use by county, from which the fraction of total Texas industrial electricity consumption used by each county was calculated. The differences in electricity consumption between the baseline and the moderate or aggressive scenarios were then

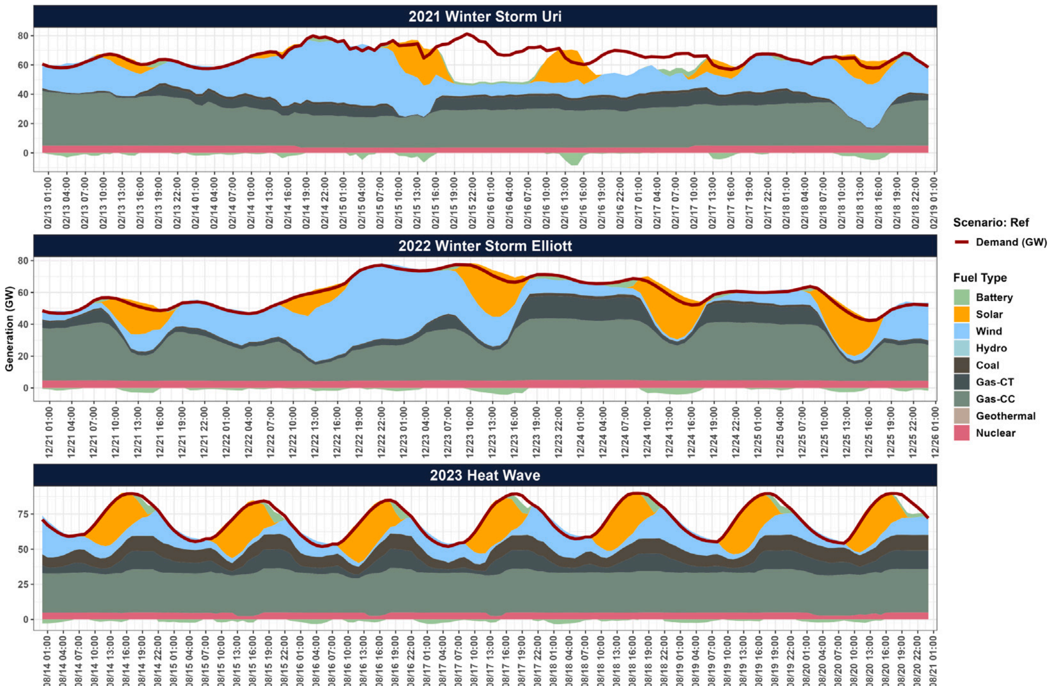

Fig. D.1. Under *Reference*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

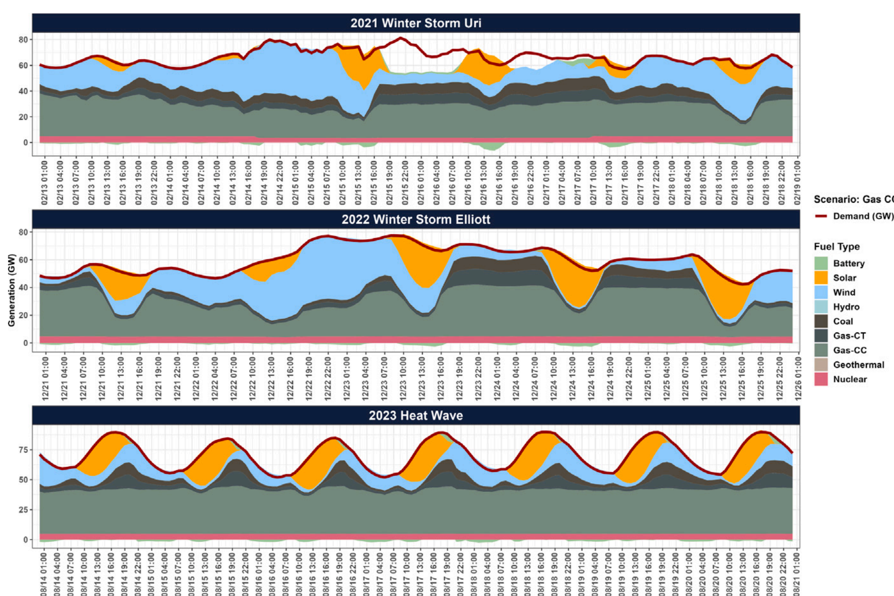

Fig. D.2. Under *Gas CC*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

multiplied by these fractions to estimate the average yearly electricity use reductions by county in 2030. County-level differences were aggregated to find changes in yearly electricity use by the ReEDS area, and hourly industrial electricity use reductions were calculated assuming industrial electricity use was temporally uniform throughout the year.

Appendix D. Grid dispatch during three extreme weather events

See Figs. D.1–D.9.

Data availability

Data will be made available on request.

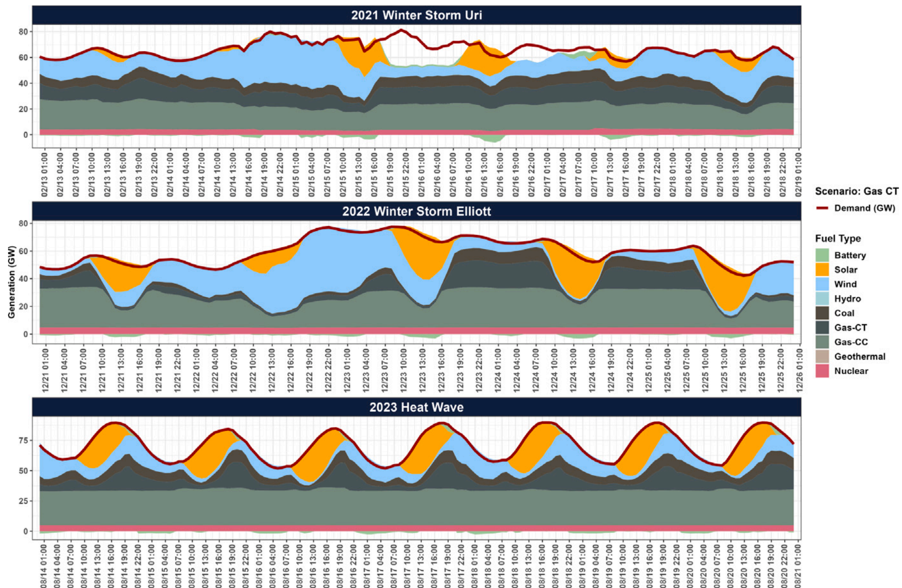

Fig. D.3. Under *Gas CT*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

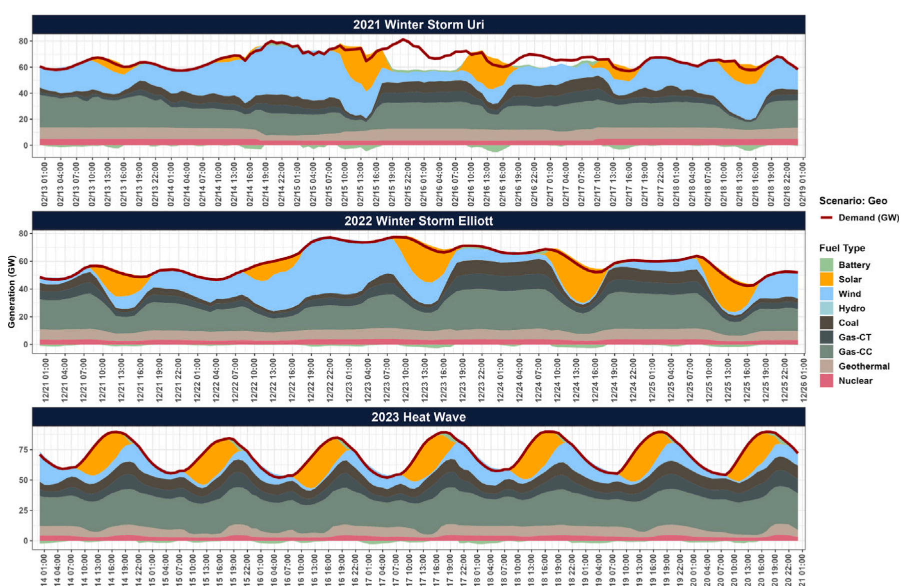

Fig. D.4. Under *Geo*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

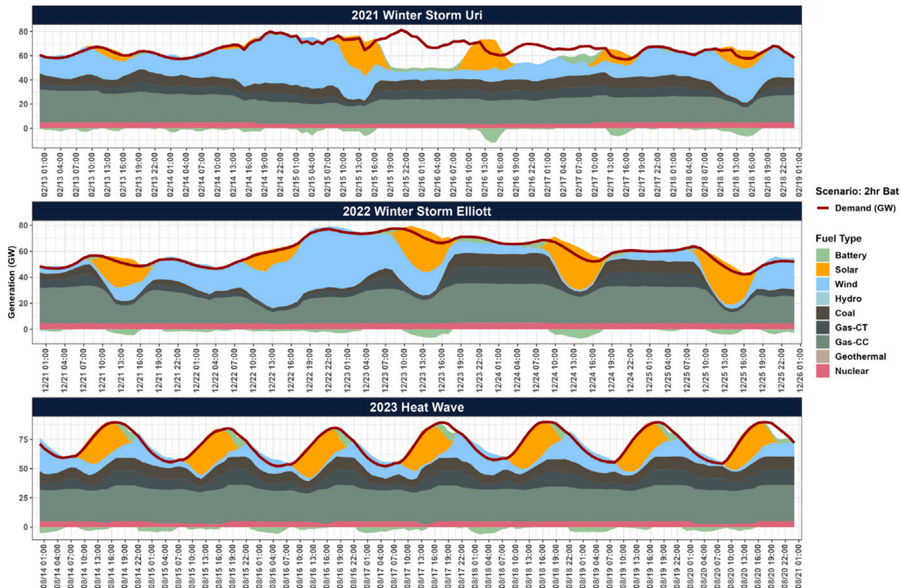

Fig. D.5. Under *2* h *Bat*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

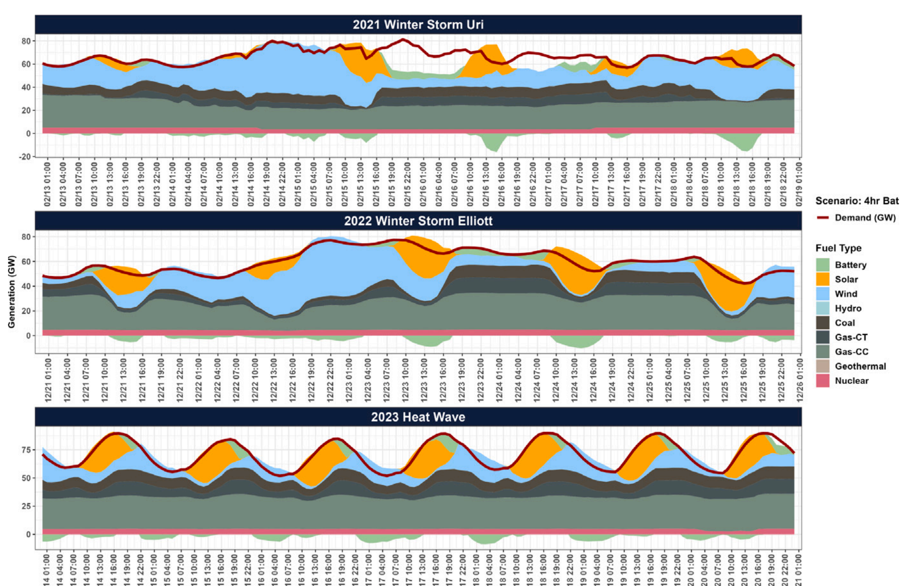

Fig. D.6. Under *4* h *Bat*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

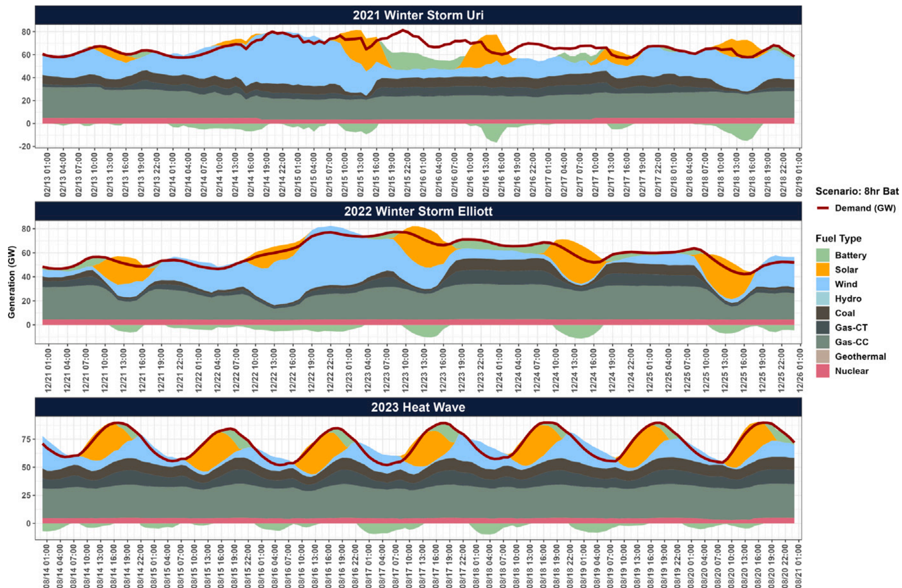

Fig. D.7. Under *8* h *Bat*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

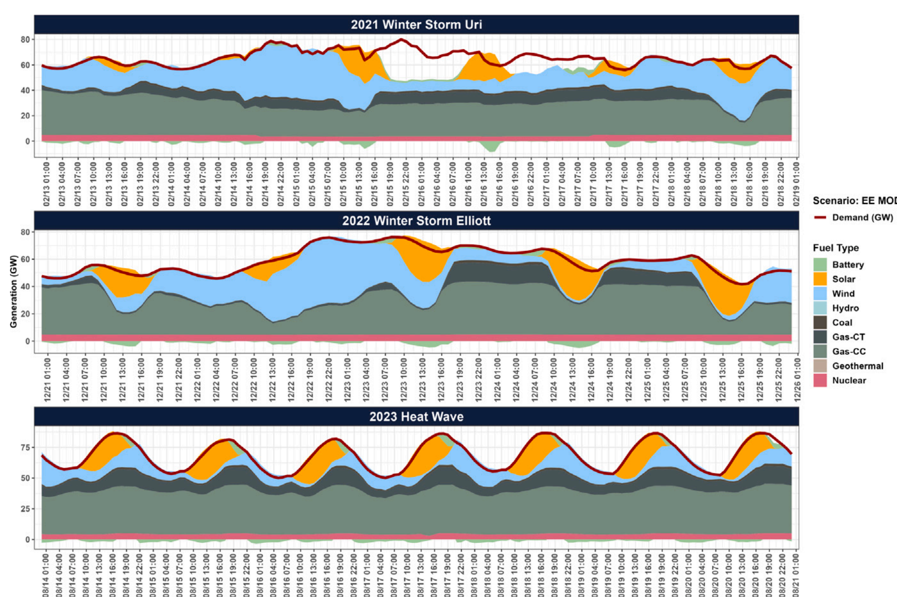

Fig. D.8. Under *EE MOD*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

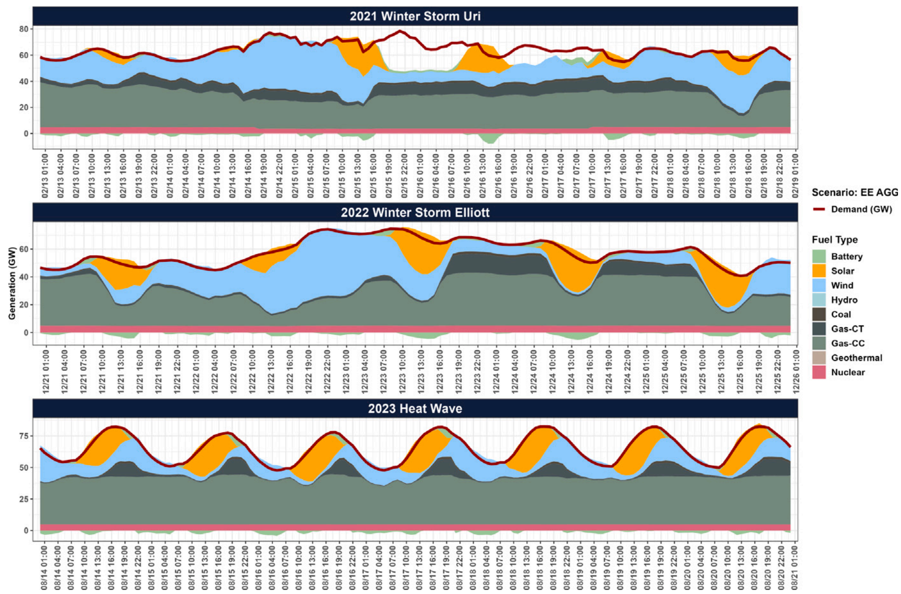

Fig. D.9. Under *EE AGG*, hourly dispatch during three extreme weather events: winter storm Uri (2021), winter storm Elliott (2022), and summer heat wave (2023) from all available grid resources. The red line indicates the projected demand at each hour.

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