Energy Efficiency & Resilience in Extreme Weather Events

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Introduction

Extreme weather events often cause economic damages and sometimes result in the loss of life. The US Department of Energy estimates that power outages and interruptions in the US cost Americans about $150 billion per year [1]. The winter storm that hit Texas in February 2021 alone resulted in hundreds of deaths and tens of billions of dollars of economic damages that will likely require decades to pay off [2]. During that winter storm, a record high demand for electricity coupled with a record high level of power system and supporting infrastructure failures left the Electric Reliability Council of Texas (ERCOT), the grid operator for most of Texas, with no choice but to institute unscheduled and involuntary firm load shed (blackouts) in a last-ditch effort to avoid a complete collapse of the grid that might have required weeks or months for full recovery. Much attention has been paid to the supply side of the problem, with a focus on freezing power plants and natural gas facilities that failed before and during the storm.

However, the demand side of electricity is just as critical as supply. Though the American Council for an Energy-Efficient Economy (ACEEE) estimated that an aggressive deployment of multiple energy efficiency and demand response programs could reduce summer and winter peaks by thousands of megawatts [3], in general, the demand side has received much less attention than the supply side. This report seeks to fill that knowledge gap by analyzing the role of energy efficiency and demand response as prospective tools to improve resilience of the energy system in Texas during future extreme weather events.

Space Conditioning

Space conditioning makes up a large portion of household energy use in the US [4] and is sensitive to ambient temperature. As a result, weather-driven space conditioning in the Texas residential sector drives seasonal peak power demand and is an important factor to understand in the context of grid resilience. Furthermore, because space conditioning is so energy-consumptive, it is worth considering for the implementation of efficiency or demand response programs.

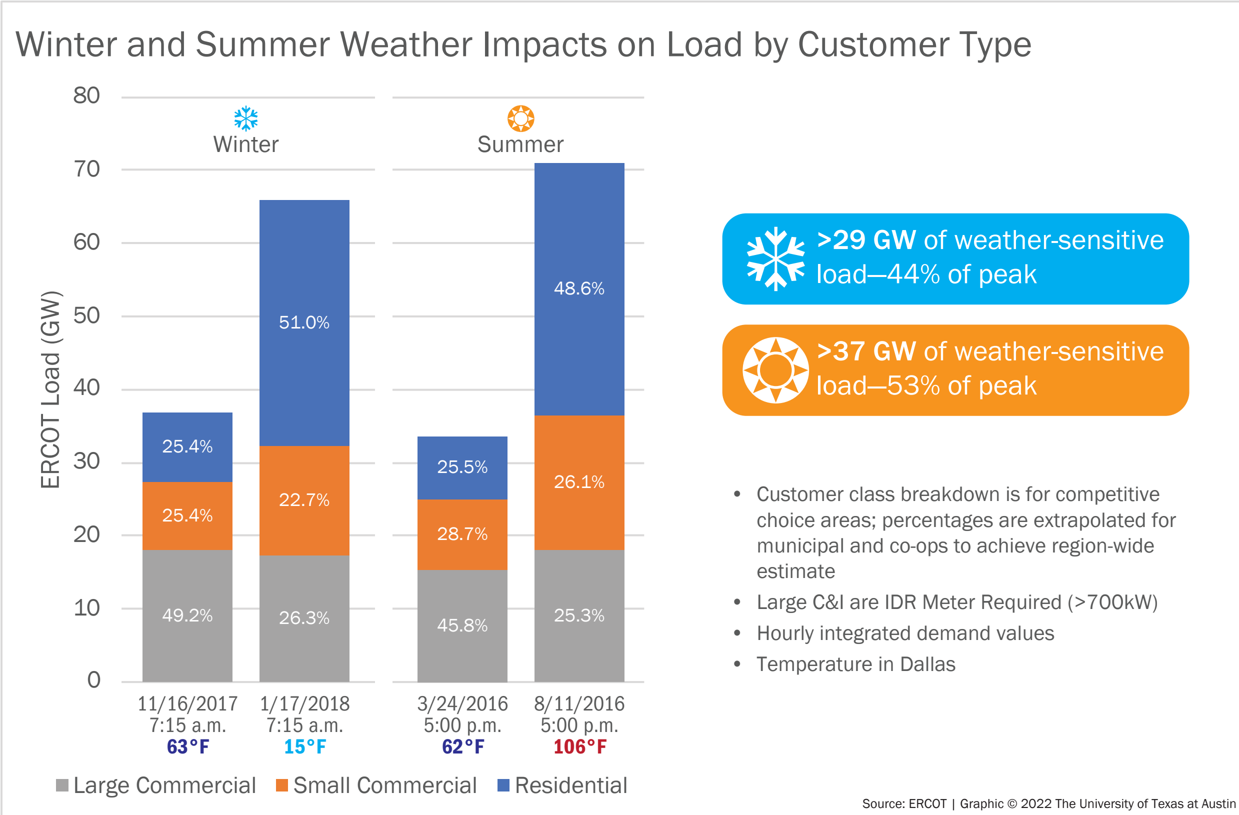

Figure 1: Figure from ERCOT showing how the residential sector in its service area changes relative to the commercial and industrial sectors during peak demand events in the winter and summer. [5] Note that the winter figure (left) and the summer figure (right) have a different vertical axis that is not shown. In both cases residential consumption is approximately half of peak power demand, with much of that variability coming from space conditioning.

For 2017, about half of the peak electrical demand in winter and summer were weather-sensitive (Figure 1). That year, 44% of the winter peak (e.g. 29 GW out of 66 GW) and 53% of summer peak (37 GW out of 71 GW) were caused by heating and cooling in response to the weather, with about 70% of that response coming from the residential sector alone. In addition, the winter sees non-electric demand increases for space or water heating, primarily from natural gas, but also from propane, oil, and wood heating systems.

To understand how peak electric demand might evolve in the future given changing weather patterns and installation of electric heating systems, it is important to understand how the grid has evolved in the past. To this end, we have developed two analyses that demonstrate 1) how the grid's response to temperature changes has itself changed and 2) how the winter peak demands are growing relative to the summer peaks. Understanding these trends helps establish the foundation for what will happen with increasing electrification of space heating, improved efficiencies of air conditioning systems, and together their potential for efficiency and demand response.

Changing sensitivity to cold weather in Texas power demand [6]

This analysis estimated the effect of heightened temperature sensitivity on electricity demand in Texas during the February 2021 blackout event. Using 20 years of hourly data, we estimated the relationship between temperature and electricity demand. We found that demand has become more responsive to cold temperatures over time, which means that cold snaps today and in the future will strain the grid more per cooling degree day (CDD) than cold snaps of decades past. This conclusion is consistent with the fact that electric heating has increased in commensurate fashion over the past 20 years in Texas. We also found that during the February 2021 event, average electricity demand was 8% higher, and approximately 10,000 MW higher during the peak hour, than it would have been had temperature sensitivity remained steady at early 2000s levels, see Figure 2. These results highlight that Texas's increased sensitivity to cold weather extremes is not limited to the supply side, but the demand side as well. These findings have implications to other regions that are seeking to reduce carbon emissions through the electrification of heating.

This analysis has been published in the journal iScience [6].

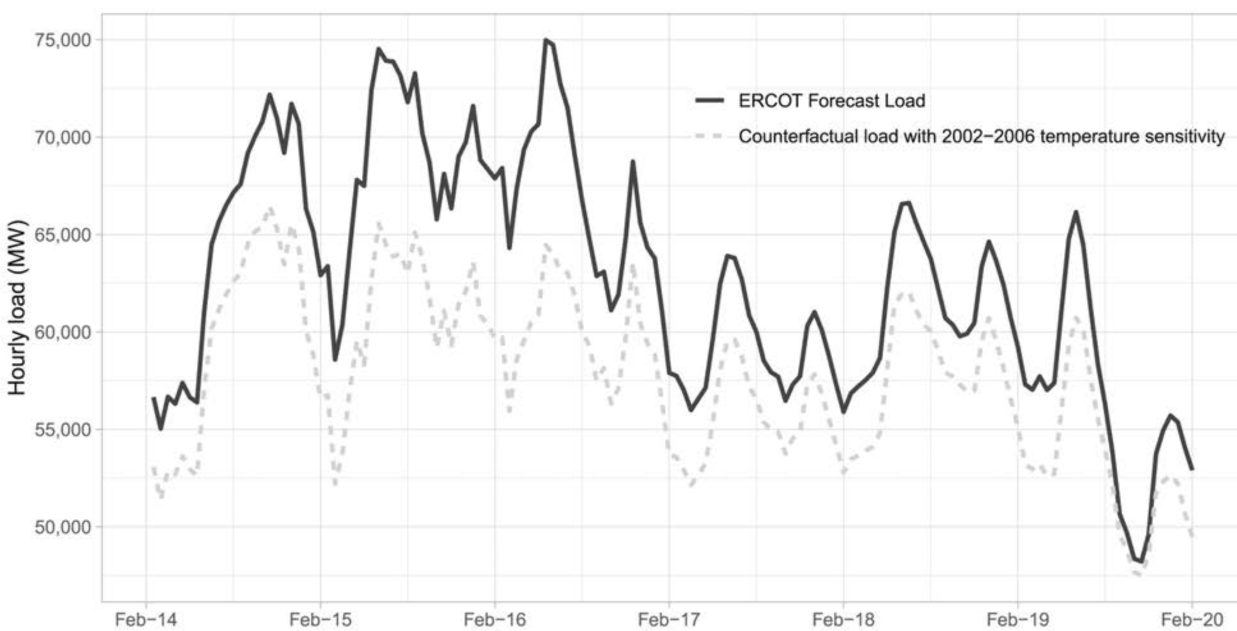

Figure 2: Load forecast and counterfactual load assessments for February 14-20, 2021 using 2002–2006 temperature sensitivity reveal that if ERCOT had had the same temperature sensitively in 2021 that it had on average from 2002-2006, then peak demand during the storm would have been lower by as much as 10,000 MW, even when adjusted for population increases.

Observations of winter and summer load growth in ERCOT and its implications for future resource planning

In addition to the role of temperature sensitivity, the evolution in summer and winter peak demands in the Electric Reliability Council of Texas (ERCOT) service area from 1997 to 2021 was quantified using a linear regression analysis. Weather data for the days in which peak demand occurred were also compiled to quantify the relationship between peak heating and cooling loads and ambient temperature. We found that the summer peak demand growth has been generally stable and approximately linear with time. Conversely, the winter peak demand growth has been less consistent, varying much more around the broader trend. This variability is likely a consequence of high residential electrical heating load on winter peak demand days, which themselves saw temperatures that varied widely from the mean value. In light of the high penetration of electrical heating equipment in Texas relative to other regions, these events may foreshadow future resilience challenges that other regions will face as heating equipment is electrified. Thus, resource planners in ERCOT should place less certainty on winter peak demand projections and an increased level of winter preparedness on both the supply and demand sectors appears warranted for resource planners in all regions.

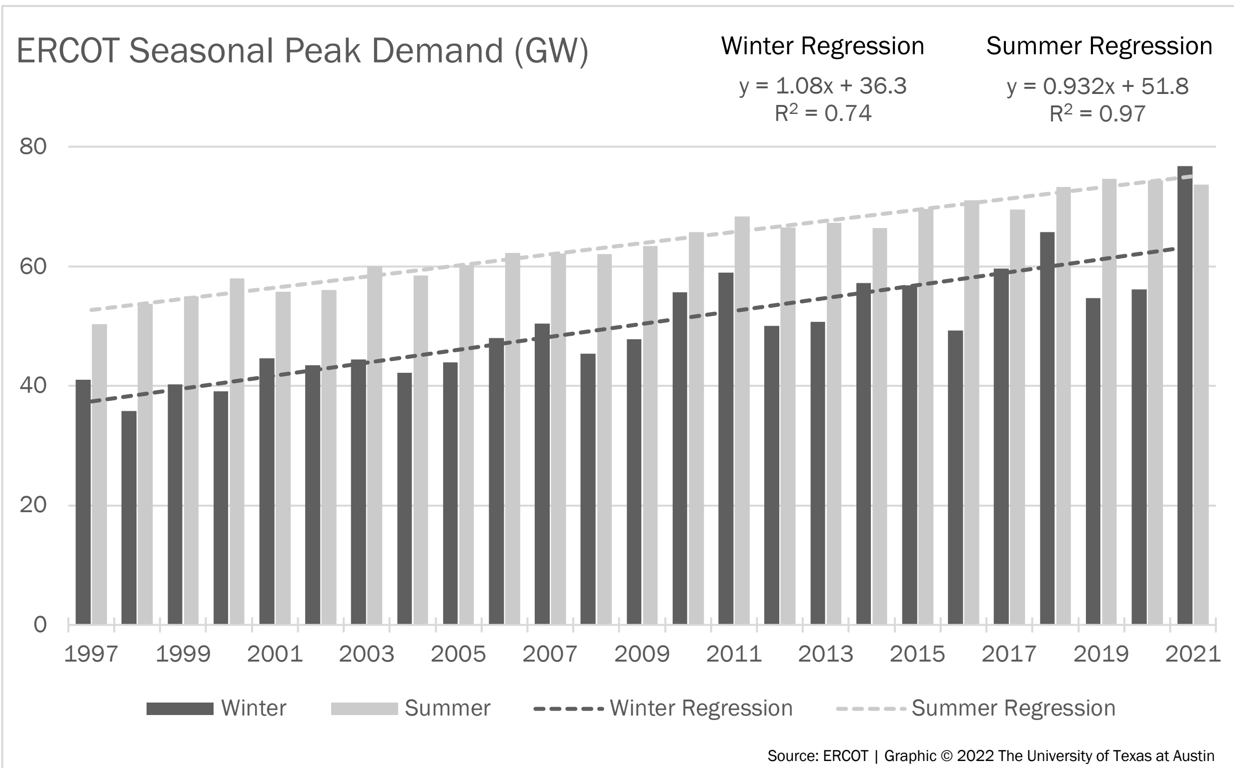

Figure 3: Figure showing the growth of winter and summer peak demand in ERCOT from 1997 to 2021. The bars are actual peak demand (or estimated peak demands if load shed happened) and the dotted lines are the linear fit estimations of peak demand for each season and each year. The winter peak demand is growing on an annual basis more quickly than the summer peak demand. The data for 2011 and 2021 show the estimate for what winter peak electric demand would have been had the grid not endured a sustained outage. Notably, 2021 was the first time that winter peak demand would have exceeded summer peak.

This linear regression shows that if trends continue the winter peak is likely to exceed summer peak regularly by the turn of the century. However, in 2021 the winter peak demand would have exceeded summer peak demand had the grid not failed during the winter storm.

This analysis has been submitted to a peer-reviewed academic journal for publication.

Additional analysis is looking at those same trends to determine how electrification might accelerate the increases in winter peak demand, and potentially slow the increase in summer peak demand (because electrified heating is usually implemented via heat pumps, which include summer performance efficiency). This technology change could accelerate the crossover point, meaning the year when winter peak demand regularly exceeds summer peak could occur sooner in the future than existing trends imply [7].

Water Heating

Just as with the expansion of electrified space heating, the same trend might occur for water heating. Water heating is already a cause of significant electric demand in Texas as 46% of water heaters in the state are electrically operated [8]. In all, about 14.7 million MWh of electricity is consumed annually in Texas for water heating, which corresponds to an average power draw of 1,680 MW [9]. That is more than the total output of a large nuclear reactor running at full capacity year-round. At a typical retail cost of $110 to $150 per MWh of electricity, Texans spend approximately $1.6 to $2.2 billion on electricity for water heating annually. Texans invest another approximately $745 million[1] for natural gas and propane for water heating, too [10]. Thus, efficiency programs for water heating represent an opportunity for cost savings for Texas households. Though the average power draw for water heating is instructive, the demand for water heating would presumably be higher in cold weather than warm weather (depending on operational patterns in the residential sector), so the contribution of water heating during winter peak times might be much higher.

[1] Population weighted ratio of natural gas and propane water heating expenditures for the West South-Central Region of the US.

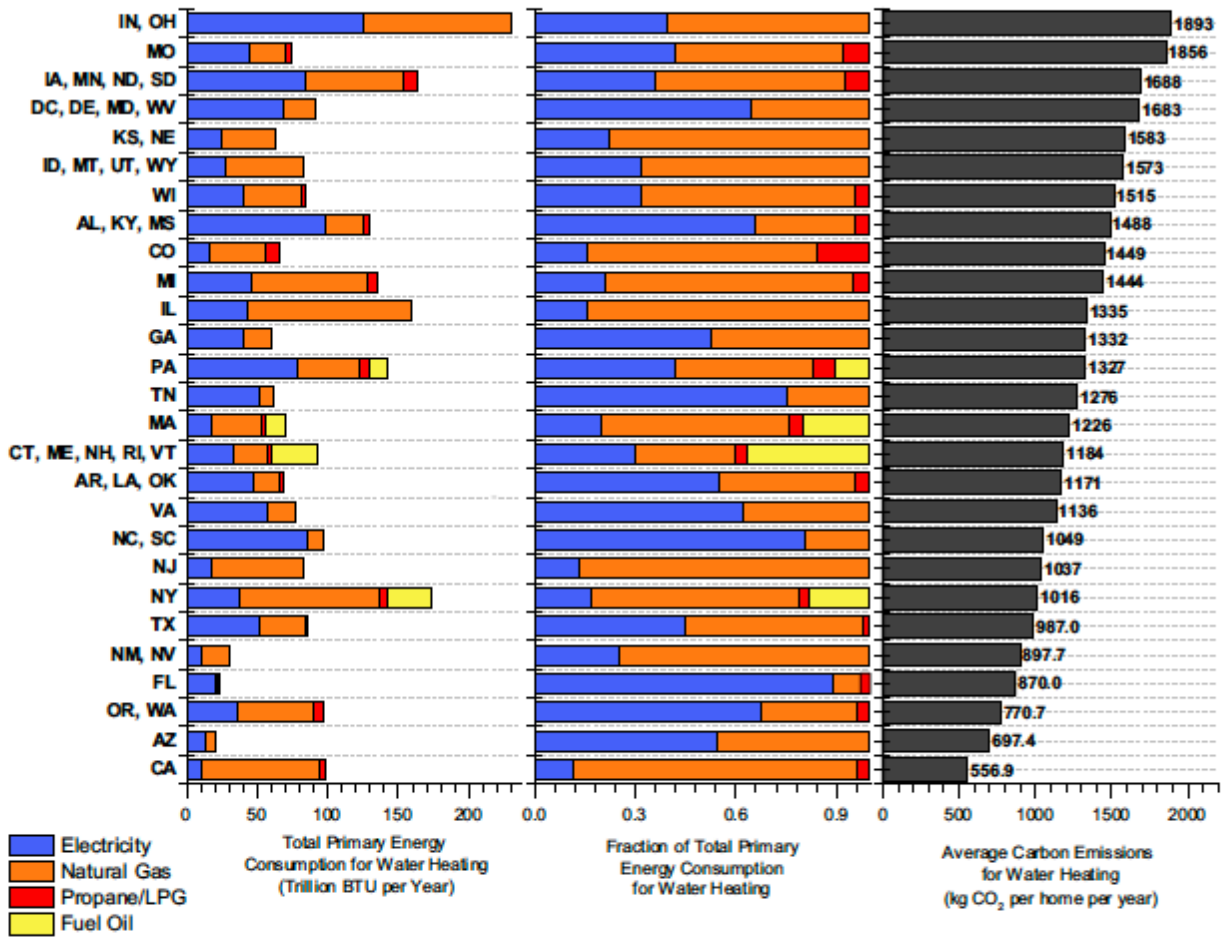

Figure 4: Texas consumes about 50 trillion BTUs (just under 15 million MWh) of electricity per year for water heating [9].

As more electric water heaters are installed, their use will simultaneously increase peak demand while also opening an opportunity for increased levels of demand response.

Electric water heaters have been successfully used for demand response programs in other countries that are roughly the same size as Texas. In France, there are more than 13 million smart electric water heater units installed. That fleet of water heaters has a nightly winter peak demand of about 8 GW, roughly the equivalent of the output from seven modern nuclear power plants. Because all the water heaters are part of the grid's demand response program, intelligently cycling them off when they are not needed enables about 3 GW of demand response for the system [11]. If a similar water heating program in Texas were to be implemented and similar ratios of demand response could be reached, then it is reasonable to expect that 500 to 1000 MW of load from water heaters could be cycled off at any given time.

Preliminary Estimates for Demand Response Potential in Texas

While there is no state-wide comprehensive demand response program or plan, there are some existing demand response programs managed by Retail Electric Providers (REPs) and of other Non-opt In Entities (NOIEs) such as electric co-ops and municipally owned utilities. In 2021, ERCOT estimated that almost 44,000 individual customers and NOIEs[2] participated in some form of demand response program, yielding over 2,500 MW in demand reduction potential during the summer months [12]. However, it was also noted in the report that most demand response programs are designed for the summer months and are focused on 4CP (Four Coincident Peak) events and thus were not available for deployment during Winter Storm Uri.

One of the NOIE areas, Austin Energy (the municipal utility for Austin, Texas) has had a demand response program called "Power Partners" since 2013 [13]. For this program, customers are given a credit or rebate and a smart thermostat, which allows the utility to cycle off air conditioners in the summer on a rotating basis to reduce peak demand. As of 2021, that program included about 43,000 controllable thermostats (32,000 smart thermostats and 11,000 thermostats controlled by one-way radio) that could reduce peak demand by about 30 MW for a cost of about $208/kW, which is much cheaper than building new power plant capacity at $1000/kW or more [14]. In the winter storm event of 2021, that same program was used to cycle off electric heat pumps to reduce peak demand.

In total, the residential sector is currently responsible for roughly half (33-35 GW) of both summer and winter peak demand periods (see Figure 1). Previous work looking at how individual appliances consume power during summer peak demand times indicates that about two-thirds of this residential use is for on-peak space conditioning [15].

The data indicate that there are about 21 GW of residential air-conditioning potentially available for demand response across the ERCOT grid during the summer peak season. If about one-third of that load were able to be shifted during peak demand times, then about 7 GW of feasible demand response potential that exists today, just for space conditioning. A demand response program at that scale could potentially obviate the need to build 7 GW of new peak capacity, avoiding billions of dollars of capital investments for power plant construction[3] and thereby representing substantial possible cost savings for consumers. Further, as the trend of the electrification of space heating continues, the winter demand potential is likely to grow. In addition, the 500 MW to 1 GW of demand response potential from electric water heating in Texas could also be included alongside smart thermostats. In both cases, the potential for demand response is growing with increasing installations of electric home heat pumps and water heaters across the state.

For these systems to tap their full potential, they will need smart controls to be installed at the appliance or meter level, customer buy-in, engagement by transmission and distribution companies, and rate schemes that reward participation (such as time-of-use or critical peak pricing or front end rebates).

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[2] Because ERCOT does not have direct access to individual customer information in the NOIE areas, the 44,000 is an underestimate of the actual number of customers that participated (likely by many tens of thousands) because customer demand response in the NOIE areas was aggregated and counted as a single entity in that report's process.

[3] At $1000 (wind, solar, etc.) to $4500 (nuclear) per kW of generating capacity for power plant construction, avoided capital investments would be on the order of $5 to $30 billion or more statewide.

Methodology

Weather dataset development

This section describes the methodology behind the evaluation of past weather events and the estimation of future weather conditions, which will drive energy use in future decades.

Past weather events

To evaluate historical weather impacts on the ERCOT grid, we compiled data for previous outages using Department of Energy form OE-417 [16]. The outages were connected to ERCOT emergency alerts and related weather reports to determine the type of weather event, including extreme cold (snow or freezes), extreme heat (high temperatures or heat wave) and drought, or high winds and precipitation. High winds and precipitation include windstorms, severe thunderstorms, tropical storms, tornadoes, and hurricanes.

Estimated future weather conditions

Future weather conditions were estimated using a series of curated climate indicators used to describe future conditions of temperature, heat, and precipitation in each of the eight weather zones in ERCOT, shown in Figure 5.

Figure 5: Map showing ERCOT's eight weather zones.

These climate indicators were produced using future climate projections and historical observations. The projections are statistically downscaled from global climate models.

Climate data used in modeling future energy use, including Near-Surface Relative Humidity, (%), Precipitation (mean of the daily precipitation rate, kg/m^2s), Daily-Mean Near-Surface Wind Speed (m/s), Daily Maximum Near-Surface Air Temperature (Kelvin), Daily Minimum Near-Surface Air Temperature (Kelvin), and Daily Mean Near-Surface Air Temperature (Kelvin), were processed from downscaled global climate models acquired from NASA Center for Climate Simulation (NCCS). These future climate markers are summarized in Table 1.

Table 1: Climate indicator inputs for modeling future energy use.

Weather Marker	Native Model Output Units
Near-Surface Relative Humidity	percentage
Precipitation (mean of the daily precipitation rate)	kg/m^2s
Daily-Mean Near-Surface Wind Speed	Meters per second (m/s)
Daily Maximum Near-Surface Air Temperature	Kelvin
Daily Minimum Near-Surface Air Temperature	Kelvin
Daily Near-Surface Air Temperature	Kelvin

NCCS describes the NEX-GDDP-CMIP6 dataset [17] as "comprised of global downscaled climate scenarios derived from the General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 6 (CMIP6) and across two of the four "Tier 1" greenhouse gas emissions scenarios known as Shared Socioeconomic Pathways (SSPs)." The CMIP6 GCM runs were generated for the Intergovernmental Panel on Climate Change's Sixth Assessment Report (IPCC AR6). The NEX-GDDP-CMIP6 dataset aims to deliver a "set of global, high resolution, bias-corrected climate change projections" in finer detail, such as at the local scale. The GCM model for this analysis is GFDL-ESM4 with SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP5-8.5 climate scenarios. In general, the modeled weather future temperatures increase as the Shared Socioeconomic Pathways number increases based on the amount of radiative forcing (heating) that the earth's climate is subjected to. Figure 6, taken from [18], shows the relative temperature anomaly given by each pathway. Note that while this analysis only considered future projections out to 2050, 2100 projections are provided for further reference.

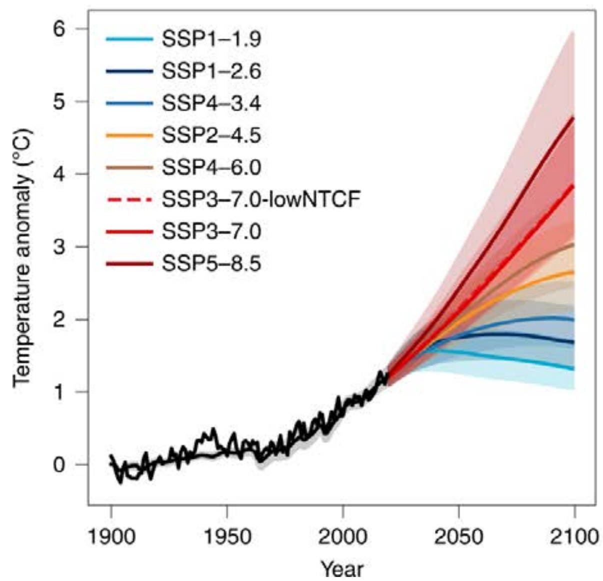

Figure 6: Global warming following SSPs with the historical temperature record from HadCRUT541 overlaid in black. Global temperature anomalies are taken relative to the 1850–1900 average. Figure and caption (side a) taken from [18].

The model used a daily original temporal resolution beginning January 1, 1950 and ending December 31, 2100. These data were then down sampled to between January 1, 2025 and December 31, 2050 for this analysis. The model used geographical resolution grid of 0.25 degrees x 0.25 degrees, processed to Texas weather zones in the ERCOT area. The future weather data projections specifications are summarized in Table 2.

Table 2: Specifications of downscaled climate model and processing used to generate climate indicators.

Category	Model Specification
GCM Model	GFDL-ESM4
Original Temporal resolution	Daily from 1950-01-01 to 2100-12-31
Temporal resolution of the processed data	Daily from 2025-01-01 to 2050-12-31
Original Spatial resolution	0.25 degrees x 0.25 degrees
Spatial resolution of the processed data	Texas weather zones in ERCOT
Climate scenarios	SSP2-4.5, SSP5-8.5, SSP1-2.6 and SSP3-7.0

These future weather data scenarios were then converted to hourly data that was used as inputs to the ResStock [19] building energy simulation model, which is further explained below.

Conversion of future daily weather data into hourly data

The future weather datasets described above included daily values of minimum and maximum temperatures, average wind speeds, average relative humidity, and average precipitation levels. However, the ResStock model, and subsequent SWITCH grid model, which is explained further below, analyses both required hourly inputs. Thus, we developed a methodology to convert the daily weather data to hourly weather data by scaling weather days (24-hour profiles) from actual 2018 weather data to approximate what the future hourly data might look like.

First, each day from the 2018 weather data was converted into a similar daily representation as that of the future climate data in Table 1. Next, the future weather data days were matched to the closest actual 2018 weather day, based on daily minimum and maximum temperatures, and the full hourly data for that 2018 weather day was used as the hourly data for the future climate day. For future days that were more than a 5% difference to the closest base weather day (2018 data), the closest day was used but the temperatures were augmented to the future daily minimum and maximum and the other hours of the day were estimated via a sinusoidal function between the two. This process was performed for all weather years and climate scenarios used in this analysis, resulting in hourly representations of the future climate data.

Updated demand curves

This section describes the methodology for developing updated demand curves from future weather scenarios for the residential and commercial sectors, energy efficiency retrofits, demand response, and district heating and cooling systems.

Residential demand

To develop future residential building energy curves, based on future weather and energy mitigation techniques, such as energy efficiency and demand response, we utilized the ResStock Analysis Tool, which was developed by the National Renewable Energy Lab (NREL) [19]. The ResStock tool can simulate energy efficiency improvements across the entire residential housing sector, which is difficult to model due to the diversity of building stock, installed equipment, resident behavior, and climate conditions.

The ResStock tool achieves this level of analysis by leveraging high performance computing applied to large public and private data sources such as the EIA's Residential Energy Consumption Survey that detail home characteristics including square footage, window-type, insulation, and HVAC equipment. The tool uses statistical sampling to generate representative building energy datasets for different target regions. Then, utilizing the DOE OpenStudio and the industry standard EnergyPlus building modeling engine, the tool generates representative building energy models. EnergyPlus is a whole building energy simulation engine that models energy consumption for HVAC, plug, lighting, and other auxiliary loads. The OpenStudio software is a collection of software used to integrate EnergyPlus with other tools to facilitate large-scale building energy modeling.

The ResStock team at NREL has used this framework to generate more than 20 million building energy simulations using statistical models of housing stock characteristics. These model runs provide detailed information on the technical and economic potential of different residential building retrofits and operational improvements. This framework allows for the identification of region-specific energy efficiency improvements with the highest potential for energy and cost savings. These analyses can then be utilized to determine how residential buildings can contribute to state energy and emissions targets.

The ResStock tool was used in multiple ways for this analysis. The tool was used to generate aggregate ERCOT-wide residential demand curves for the existing housing stock, projected out for 2050 using current weather patterns and updated future weather projections as previously outlined. These runs involved the simulation of 1,383 homes to represent the ERCOT residential building stock. The impacts of a suite of energy efficiency upgrades were also simulated, including increasing the attic insulation levels to a minimum of R-38, upgrading windows to dual-pane Low-E units, decreasing outside air infiltration to 7 ACH50, as well as swapping out the existing heating and cooling systems to SEER 18, 9.3 HSPF efficiency heat pumps.

These new profiles were substituted for the existing residential building profiles in the overall ERCOT load by considering that, based on Figure 1, residential demand constitutes about 50% of overall total peak demand. The ResStock residential demand profiles generated (for the simulation of the 1,383 homes using actual weather year data for 2018, with no additional efficiency upgrades) were scaled up such that the aggregate value of residential demand was half of ERCOT's 2018 peak demand, then both were scaled to 2050 values assuming an annual 1.8% growth.

Next, it was then possible to remove the 2050 residential demand profiles (based on today's weather) and substitute in alternative (future climate scenario and efficiency upgrade combinations) future weather demand residential profiles which were scaled based on the increases or reductions in energy use from the ResStock analysis.

Commercial demand

To assess the impact of energy efficiency measures in the commercial building stock, we utilized the difference in energy use from the residential sector as a benchmark for estimating the change in commercial building energy use over the same period. Given that the change in commercial demand from low consumption periods to high consumption periods is roughly half that of residential demand (see Figure 1), we estimated that the impact of similar energy retrofits and climate scenarios would produce roughly half as much of a change as to the residential sector and scaled that portion of demand accordingly in the total ERCOT profiles.

Demand response

We modeled demand response as an input to the grid model, but assumed that it would include reductions in space conditioning and water heating during peak grid times. We assumed that, by 2050, demand response would reduce the ERCOT-wide peak demand by 5% (a conservative possibility given the potential is much higher) and demand response measures in the ERCOT market would take effect whenever demands were within 95% to 100% of peak demand over all times of the year. For example, if peak demand were 100 GW, we assumed that demand response reduced the peak to 95 GW and that all times of demand between 95 GW and 100 GW were also reduced to 95 GW.

District heating and cooling demand in the residential sector

We also developed future scenarios where the majority of residential heating and cooling demand were switched to district heating and cooling systems. Because residential energy use includes some non-space conditioning demands (such as lighting, computers, media consoles, etc.), we assumed that the first quartile of hourly demands represented this value, which roughly corresponds to values shown in Figure 1. The assumed non-HVAC “baseload” demand curves were very similar across each of the ResStock modeling runs that incorporated future climate scenarios. This similarity indicated that these baseload values were not meaningfully impacted by increasing the efficiency of the building envelope or HVAC systems. Thus, we then took the daily energy use above these baseload values as the space conditioning loads and aggregated them to daily summed energy for heating and cooling. These daily energy values were then evenly distributed over all hours of the day to simulate the ability of the district heating and cooling systems to provide space conditioning services via a flat load instead of individual heaters and air-conditioners ramping up and down throughout the day.

Electric vehicle load growth

To estimate the amount of electric vehicle charging that would be added to the aforementioned traditional loads, we developed a 24-hour curve of EV demand based on ERCOT’s 2018 Long-Term System Assessment for the ERCOT Region (LTSA) that forecasts ERCOT electric vehicle charging behavior in 2033 [20]. We assume that electric vehicles will charge according to this 24-hour pattern for each day of the year. To develop curves for years before and after 2033 (2020-2050), we assumed that the charging pattern scales linearly from no charging in 2015.[4] Under this assumption, the electric vehicle load in 2015 is zero, in 2024, it is 50% of the 2033 ERCOT profile and in 2042 it is 150% of the 2033 ERCOT profile. These daily EV charging profiles are shown in Figure 7. Next, we distributed the total electric vehicle charging profile among the 16 transmission regions based on population, adding the EV charging profile to each region’s hourly load profile.

[4] We recognize that there was some EV charging before 2015 but assumed it to be small relative to future EV demands.

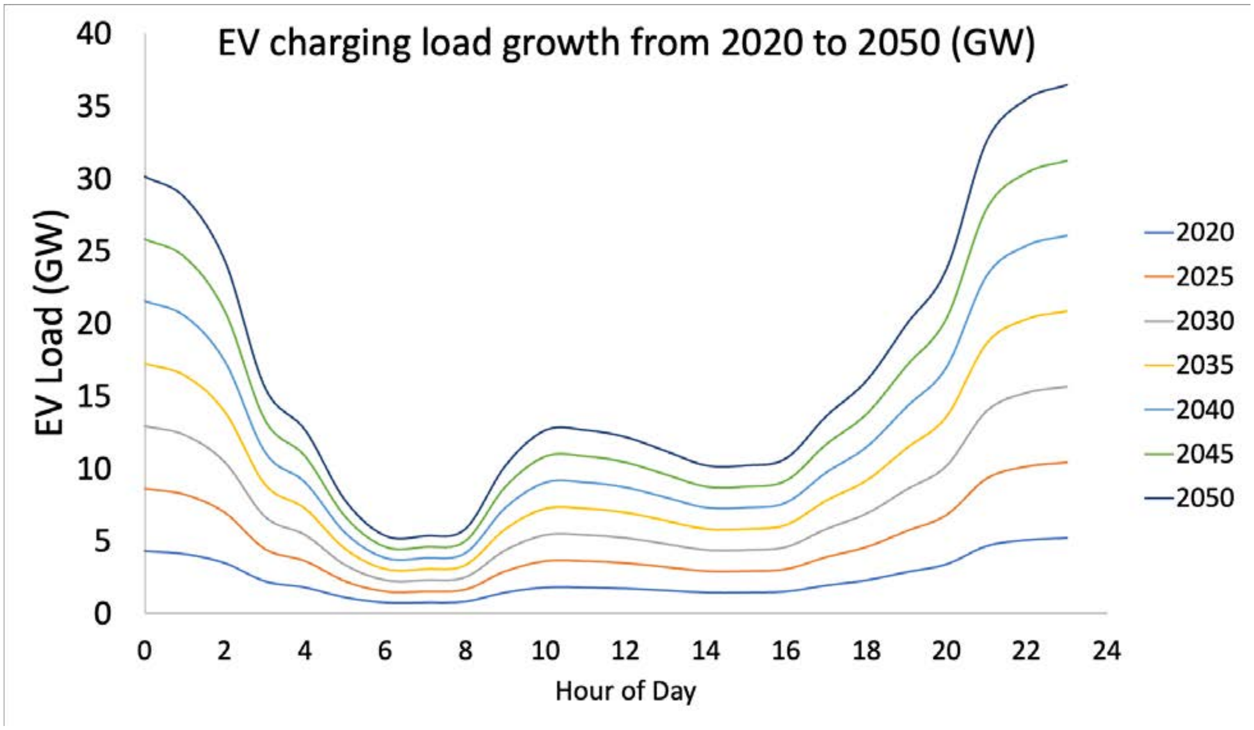

Figure 7: Figure showing the daily assumed EV charging loads from 2020 to 2050.

Distributed solar growth

We calculated the impacts of distributed solar growth in a similar way to that of EV loads, except their generation profiles were subtracted from the total load profiles in each region. We began with ERCOT's LTSA assumption that the region would see 5 GW of distributed solar by 2033. As for electric vehicles, we assumed that the distributed solar profile scales linearly from 2015 (~0 GW)[5] and growing to 2.5 GW in 2024, 7.5 GW in 2042, and almost 10 GW by 2050. Next, the distributed solar capacity was allocated amongst the 16 transmission regions of the grid model, described in the next section, based on population.

These regional distributed solar generation profiles were then subtracted from the traditional load + EV load curves to generate the final demand curves that were used as inputs to our ERCOT grid model to assess their impacts on grid development and operations.

Updated ERCOT demand curves for grid modeling

The potential changes to future demands described above resulted in 30 versions of ERCOT's 2050 hourly demand. Because the grid model simulates multiple intermediate time periods between the present and 2050, hourly values from 2020 to 2050 were linearly interpolated to develop intermediate hourly demand profiles for the years 2025, 2030, 2035, 2040, and 2045. These multiple years of hourly demand profiles were used as demand inputs to the grid model.

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[5] We acknowledge that there was distributed PV on the ERCOT system before 2015 but assumed it to be small relative to future deployments.

Electric grid impacts

The following describes the methodology around the development of the model used to assess the grid impacts of efficiency and demand response measures as developed above.

ERCOT grid model

The UT team has developed a capacity expansion model of the ERCOT electricity grid based on the open-source SWITCH 2.0 platform [21]. A capacity expansion model is an optimization program that makes decisions about the operation and construction of power plants, transmission lines, and other electric grid assets in a least cost and optimal way. The model accomplishes this task on both short and long-term time scales. On the short-term, the model dispatches the power plant fleet within each time period so that electricity generation and electricity demand are balanced for each hour of the simulation. Over the long-term, or between each time period, the model builds new power plant capacity to 1) provide enough power plants so that electricity generation and demand growth can be balanced in future years including with a target reserve margin, and 2) enable the composition of the power plant fleet to evolve in ways that minimize the total system cost or to meet user-specified constraints, such as carbon emission reductions.

The ERCOT model was built using data about the existing power plant fleet and transmission capacity from ERCOT's Seasonal Assessment of Resource Adequacy (SARA) and Capacity, Demand and Reserves (CDR) reports [22] as well as transmission line data from the Department of Homeland Security [23]. Demand data have been aggregated from historical ERCOT load curves [24] as well as edited by the methodology discussed above and apportioned by population to a 16-zone load and transmission topography shown in Figure 8. More details about the grid model construction and input assumptions can be found in Appendix D.

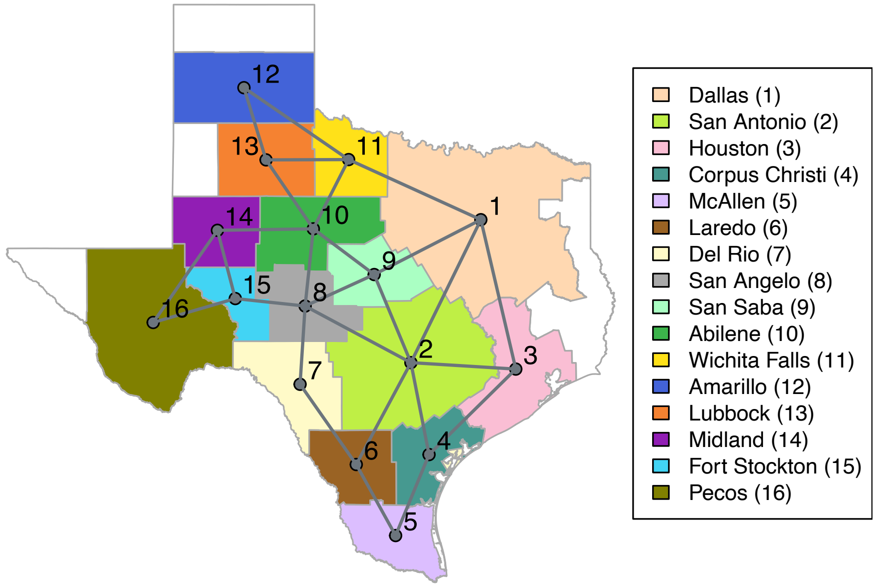

Figure 8: Figure showing the load zones and transmission connections of the ERCOT capacity expansion model used in this analysis.

The results from each modeling run include the total amount of costs to operate the system, the dispatch of each power plant, the new infrastructure built, and the total amount of electricity generated by each fuel type [25].

Model and dataset integration

In summary, the updated weather datasets led directly to new demand curves as peak demands in Texas are largely driven by space conditioning loads. As temperature profiles change, so will the energy demand of the buildings that are looking to keep their occupants comfortable. These demand profiles are further changed by the deployment of distributed solar PV systems and electric vehicles. Then, the impacts of weather and other technologies, multiple energy efficiency measures were considered to temper the impacts of generally hotter and drier summers.

The lessons learned from the analysis above can then be used to inform the discussion around the building code and energy assurance plan in a meaningful way.

Building code and Energy Assurance Plan

The building codes active across Texas cities and at the state level, as well as the codes that have been passed since Texas's adoption of the 2015 IECC codes, were reviewed. Relevant building code literature has been reviewed, including building code analyses conducted by the Department of Energy. The review also incorporated climate-friendly policy recommendations that would contribute to making residences and commercial buildings safer in more extreme weather.

In addition to building codes, weatherization strategies were reviewed. Community action agencies across the state from multiple ERCOT weather zones were contacted to understand the most needed strategies in homes participating in the Weatherization Assistance Program and the Low-Income Home Energy Assistance Program.

Finally, the team has made recommendations to update the Energy Assurance Plan (EAP) from current technologies and policies of 2012 to those of 2022 using the current EAP Table of Contents. Relevant literature relating to statewide energy sector recommendations since February 2021 that might improve the current Energy Assurance Plan that was published in 2012 following the 2011 winter storm was reviewed.

Results

Weather datasets

The following sections describe how historical weather patterns have impacted energy customer outages as well as how future weather patterns might deviate from today.

Past weather events

US Department of Energy OE-417 reports show over 200 occurrences of power outages in Texas associated with extreme weather events, including hurricanes, tropical storms, extreme heat, and extreme cold from 2002 to 2021 [16]. Most weather-related outages occur during extreme wind or precipitation events such as hurricanes, tornadoes, tropical storms, or less severe instances of high wind and precipitation. For example, Hurricane Harvey caused multi-day outages across the Texas Gulf Coast in 2017.

Heat or high temperature related outages occurred in 2006 (1 day), 2008 (3 days), 2010 (2 days), 2011 (16 days), 2015 (3 days), 2016 (6 days), and 2019 (4 days). Extreme cold related outages occurred in 2010 (5 days), 2011 (5 days), 2012 (4 days), 2014 (3 days), 2018 (4 days), 2020 (1 day), and 2021 (18 days) as shown in Table 3. The effects of Winter Storm Uri in 2021 caused two additional days of outages in June from tight grid conditions due to the high number of forced generation outages [26].

Table 3 Grid outages related to extreme heat or cold events in ERCOT between 2006 and 2021. Outages caused by hurricanes, tornadoes, tropical storms, or less severe instances of high wind and precipitation are not included.

Year	Extreme Heat	Extreme Cold	Note
2006	1	--	
2007	--	--	
2008	3	--	
2009	--	--	
2010	2	5	
2011	16	5	Major winter storm and heat wave/drought
2012	--	4	

2013	--	--	
2014	--	3	
2015	3	--	
2016	6	--	
2017	--	--	
2018	--	4	
2019	4	--	
2020	--	1	
2021	--	20	Winter Storm Uri caused outages in February and forced outages in June due to repairs

While the number of days that power plants are impacted by weather is similar between extreme heat and cold events, the number of customers and the length of time for which they were impacted is very different. Cold-related events generally impact more customers for longer. The data indicate that customers are affected for much longer amounts of time due to power outages incurred due to extreme cold than extreme heat, as shown in Table 4.

Table 4: Total reported customers impacted and total hours of outage for heat- and cold-related outage events in ERCOT by year.

	Year	Total Hours	Total Customers Impacted
Heat-related Outages	2006	11	750,882
	2010	16	81,586
	2011	286	294,064
Cold-related Outages	2010	117	552,999
	2011	63	1,393,743
	2012	119	504,509
	2021	896	5,276,732

Estimated future weather conditions

The average for the years 2030-2039 and 2040-2049 of maximum daily temperature estimated in the NEX-GDDP-CMIP6 dataset, downscaled to the ERCOT weather zones is shown in Figure 9. While only a decade different, the maximum daily temperatures in the 2040s are generally higher than the maximum daily temperatures in the 2030s across all weather zones. However, maximum daily temperatures in late fall in the coastal, eastern, and southern weather zones are lower in the 2040s compared the 2030s.

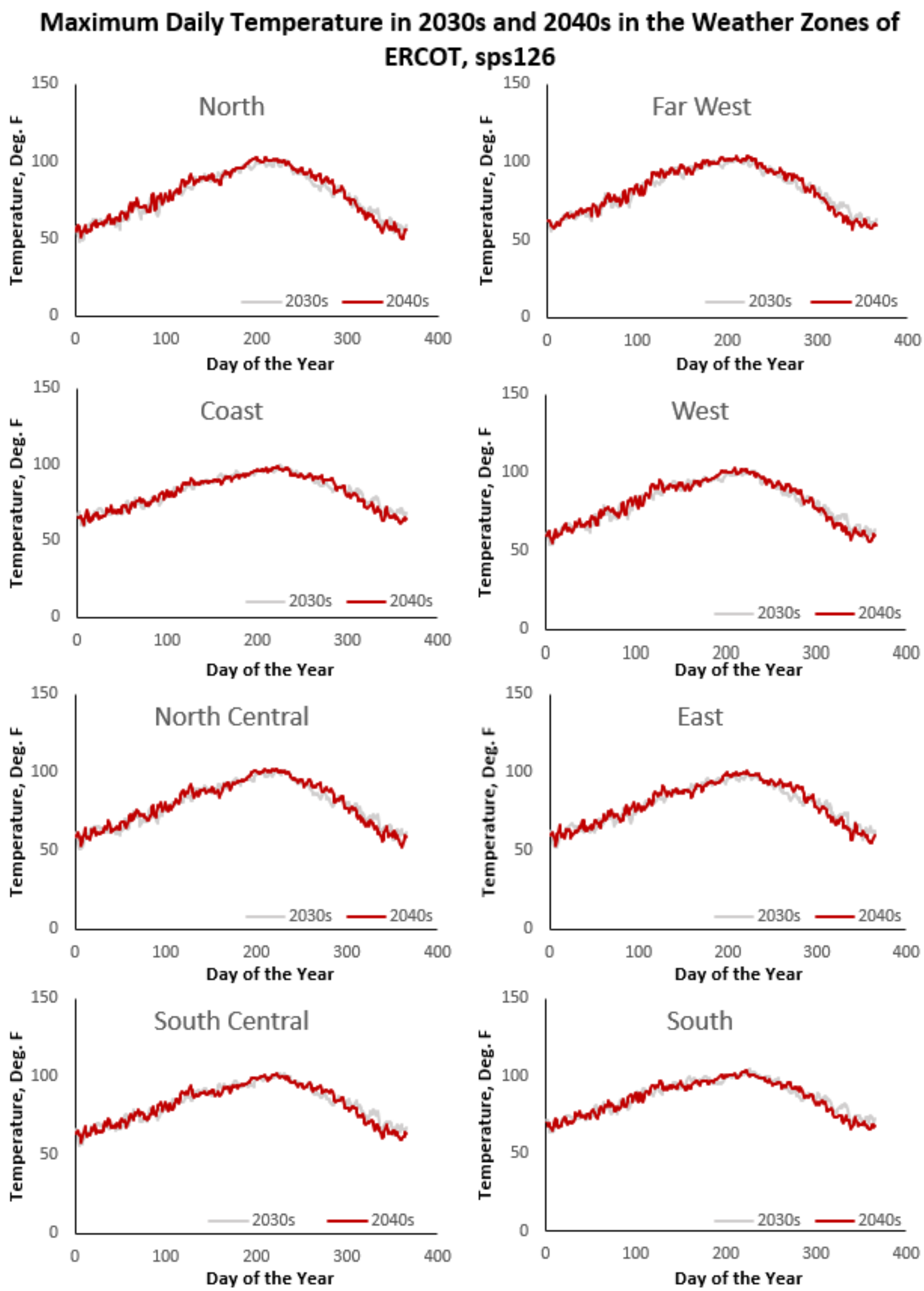

Figure 9: Figure. Maximum daily temperature estimated for 2030s and 2040s in the weather zones of ERCOT, estimated via CMIP6, SSP1-2.6.

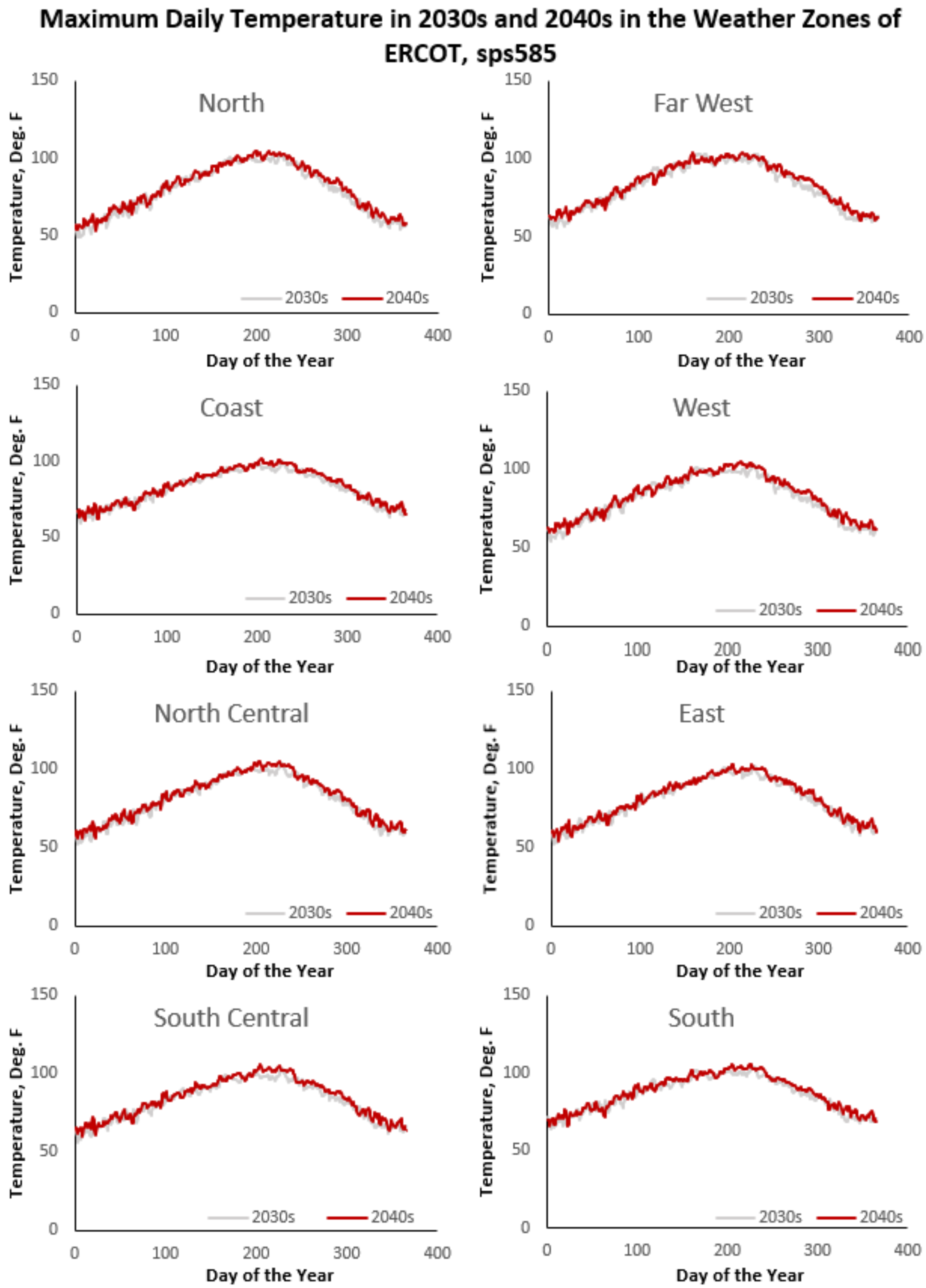

Figure 10: Figure. Maximum daily temperature estimated for 2030s and 2040s in the weather zones of ERCOT, estimated via CMIP6, SSP5-8.5.

While risk of extreme winter events was not modeled in this work, the team consulted State Climatologist John Nielsen-Gammon. Extreme winter weather events can be expected with a frequency of 1 in 20 currently. Over the next century, that risk is expected to reduce to 1 in 50. While the frequency is lower, it is still within a range to plan for, particularly because of the extreme impact and damage of winter storms. Complacency can increase that impact.

Demand curve development results

This section discusses the results of the demand curve development analysis as described in the Methodology section.

ResStock results

The ResStock modeling sought to assess the effect of two types of impacts on residential energy use: future weather conditions and energy efficiency upgrades. Note that the following figures in this section are results from simulations of a representative subset of residential buildings in the ERCOT region (1,383 homes) before they were scaled up to the entire residential sector of approximately 9 million homes. Figure 11 shows the impact of future weather scenarios on the energy use of residential buildings in the ERCOT region assuming a baseline of no energy efficiency upgrades.

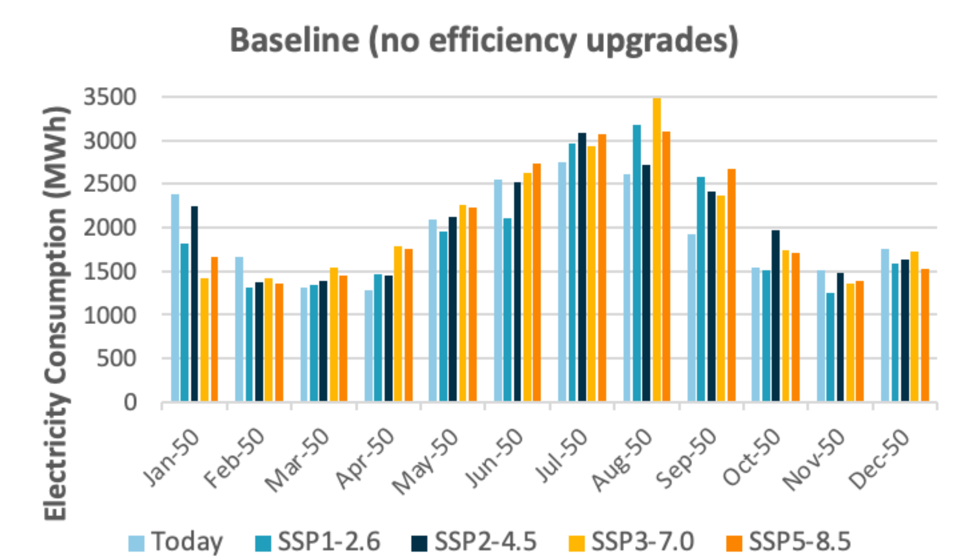

Figure 11: Figure showing the impact of future weather scenarios on residential energy consumption in ERCOT in 2050.

In general, residential energy use in future weather scenarios decreases during the colder months and increases during the warmer months. This pattern is consistent with temperatures generally increasing in the future in both the summer and winter months. Relative to today's weather[6], the mildest future weather year (SSP1-2.6) is estimated to have lower overall energy use in the residential sector, with a decrease of about 1.1% by 2050, all else equal and assuming

[6] 2018 actual weather data used.

no energy efficiency upgrades. This outcome is mainly due to lower overall energy use in the winter and shoulder months which offsets higher use in the warmer summer months. However, the other climate scenarios (SSP2-4.5, SSP3-7.0, and SSP5-8.5) suggest higher overall energy use, between 4.6% and 5.6% higher than the baseline of today's weather.

Figure 12 shows a similar plot to Figure 11, but assuming that all homes in the ERCOT region undergo a suite of energy efficiency upgrades by 2050 such that, by 2050, all homes in ERCOT have a minimum attic insulation level of R-38, dual-pane Low-E windows, and have been air-sealed to an air infiltration rate of 7 ACH50, appliance upgrades are considered further down. Additional appliance level efficiency upgrades, such as upgrading water heaters could also provide efficiency gains across the building stock.

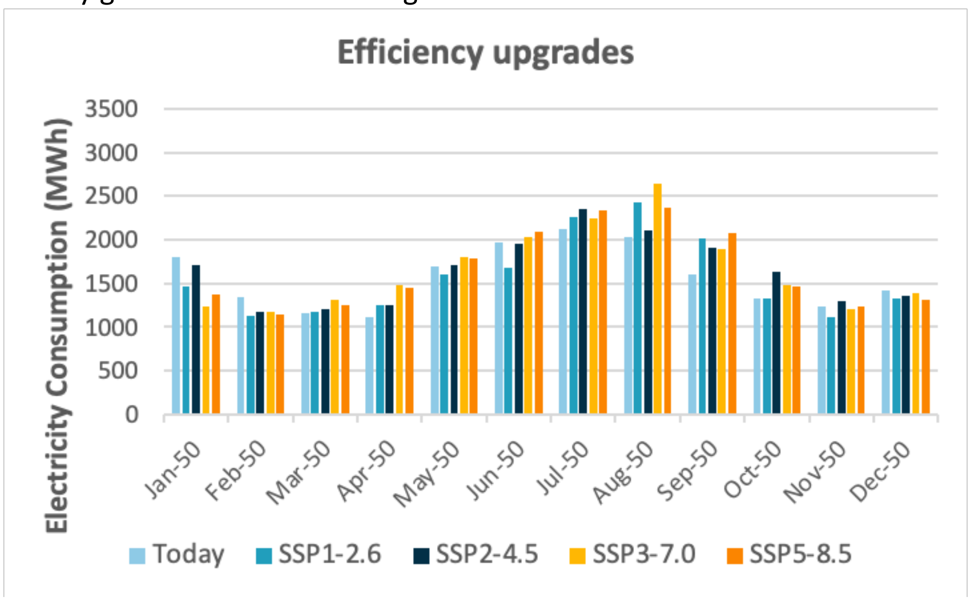

Figure 12: Figure showing the impact of future weather scenarios on residential energy consumption in ERCOT if homes were to have a suite of energy efficiency measures deployed by 2050.

Energy efficiency measures significantly reduced energy use from baseline values by an average of about 20% across today's weather and all future weather scenarios, which is substantial. Within the energy efficiency scenario (values in Figure 12), the future weather scenarios followed a similar pattern to the baseline case with the mildest scenario (SSP1-2.6), yielding less energy use (-0.1%) than the today's weather scenario while the other climate scenarios caused higher energy use, relative to today's climate, of between 4.2% and 5.7%.

Figure 13 shows the same data as Figure 12, but in addition to the energy efficiency upgrades, all HVAC units in the ERCOT housing stock have been replaced with SEER 18, 9.3 HSPF efficiency heat pumps.

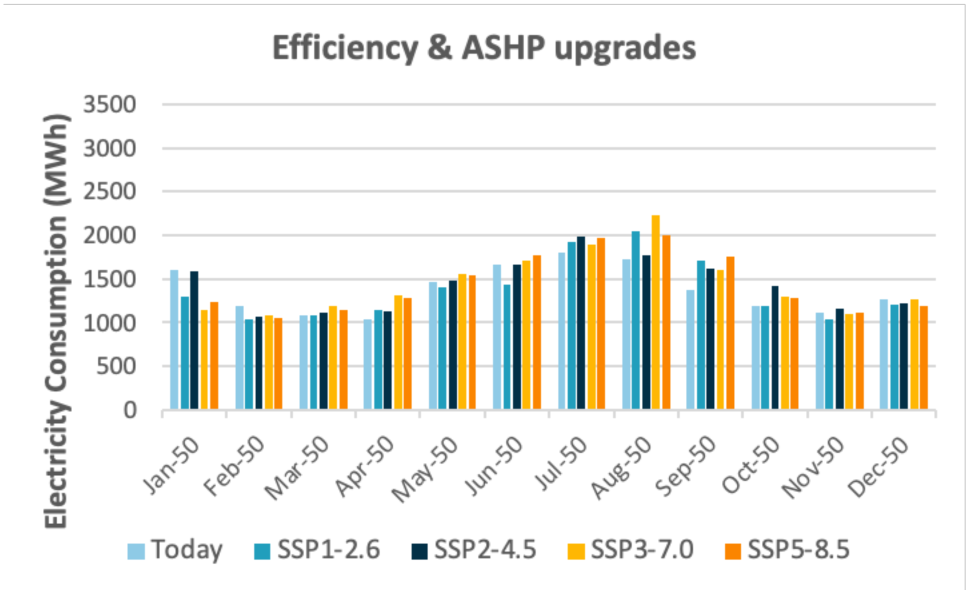

Figure 13: Figure showing the impact of future weather scenarios on residential energy consumption in ERCOT if homes were to have a suite of energy efficiency measures and energy efficient heat pumps deployed by 2050.

Relative to a baseline of no energy efficiency upgrades, the residential building energy efficiency upgrade and heat pump scenario uses about 30% less energy in 2050. Within this scenario, all future climate scenarios use more electricity when compared to today's weather, between 0.1% more (SPP1-2.6) and between 4.4% and 5.7% more for the other climate scenarios.

Figure 14 through Figure 18 show the impact of energy efficiency and heat pump upgrade measures on electricity use for all considered weather scenarios. In general, without energy efficiency measures, energy use increases with warmer future weather conditions. However, even under the warmest of future weather scenarios considered, energy efficiency measures are able to counteract the warmer weather and can actually reduce overall energy use to levels below the scenario of no efficiency upgrades and today's weather.

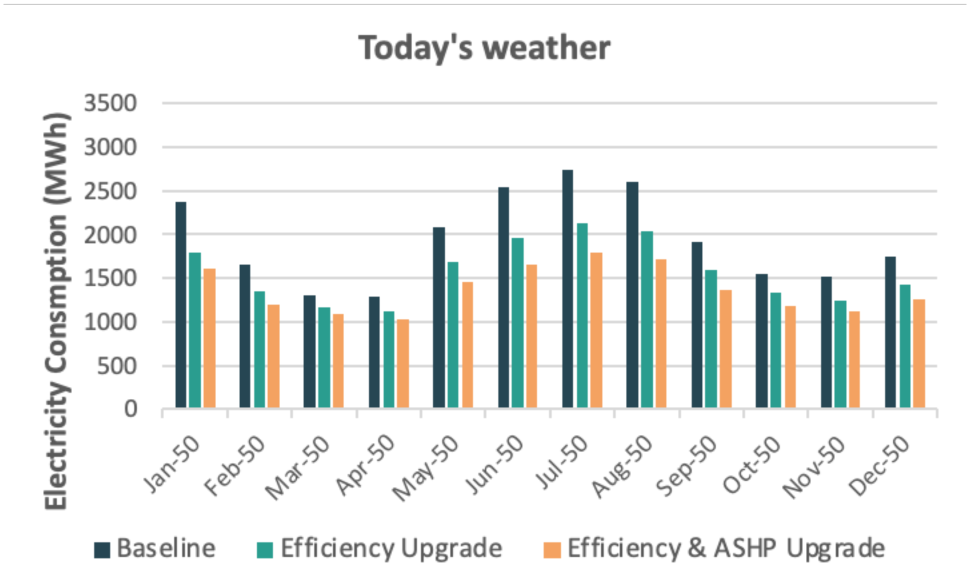

Figure 14: Figure showing the impact of efficiency upgrades alone and efficiency upgrades paired with heat pump upgrades utilizing today's weather for a representative sample of residential buildings in ERCOT.

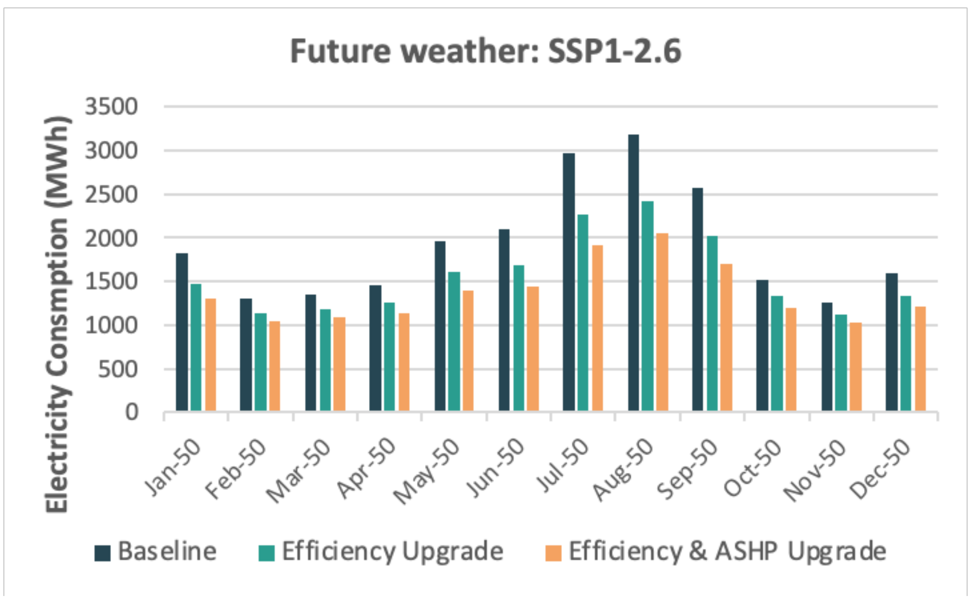

Figure 15: Figure showing the impact of efficiency upgrades alone and efficiency upgrades paired with heat pump upgrades utilizing future weather scenario SSP1-2.6 for a representative sample of residential buildings in ERCOT.

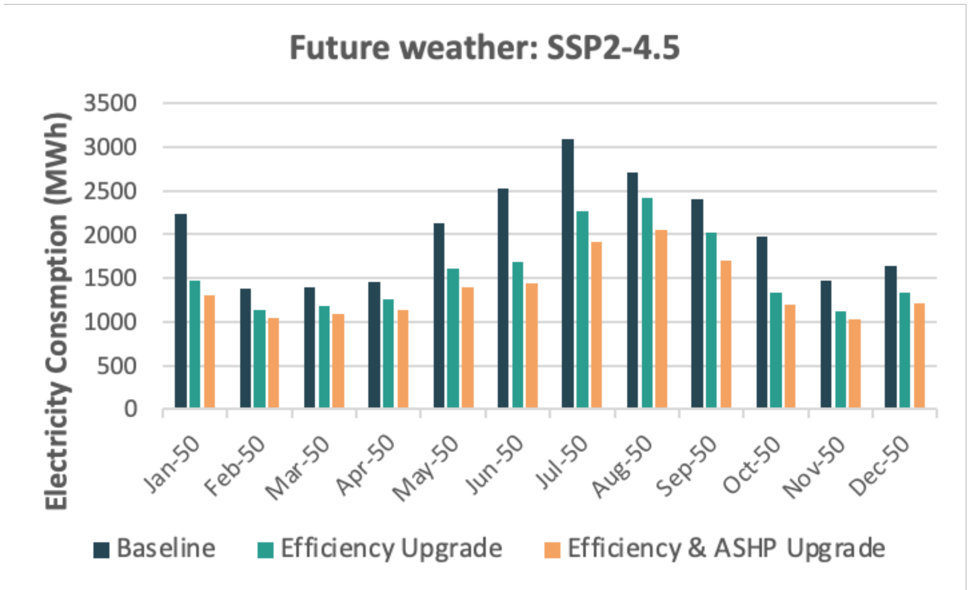

Figure 16: Figure showing the impact of efficiency upgrades alone and efficiency upgrades paired with heat pump upgrades utilizing future weather scenario SSP2-4.5 for a representative sample of residential buildings in ERCOT.

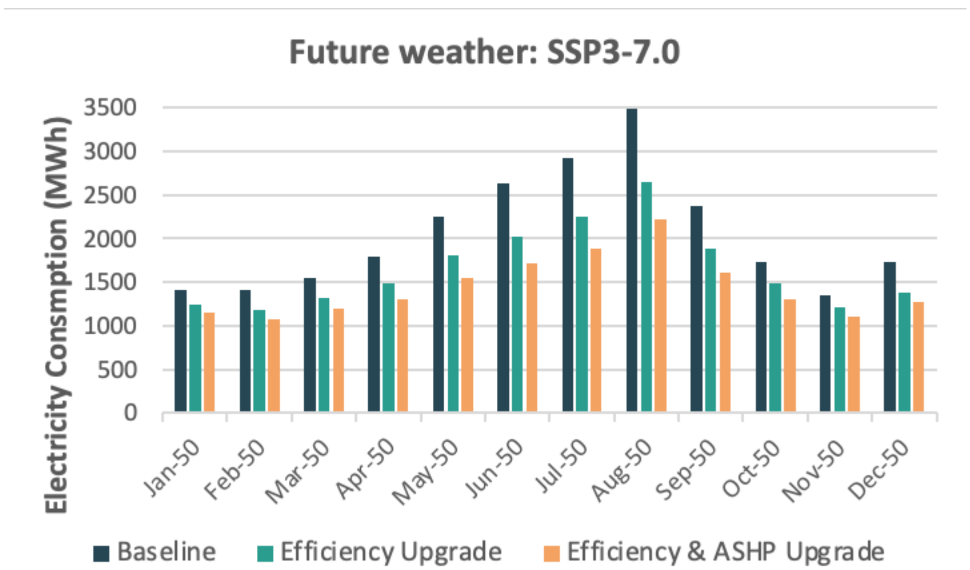

Figure 17: Figure showing the impact of efficiency upgrades alone and efficiency upgrades paired with heat pump upgrades utilizing future weather scenario SSP3-7.0 for a representative sample of residential buildings in ERCOT.

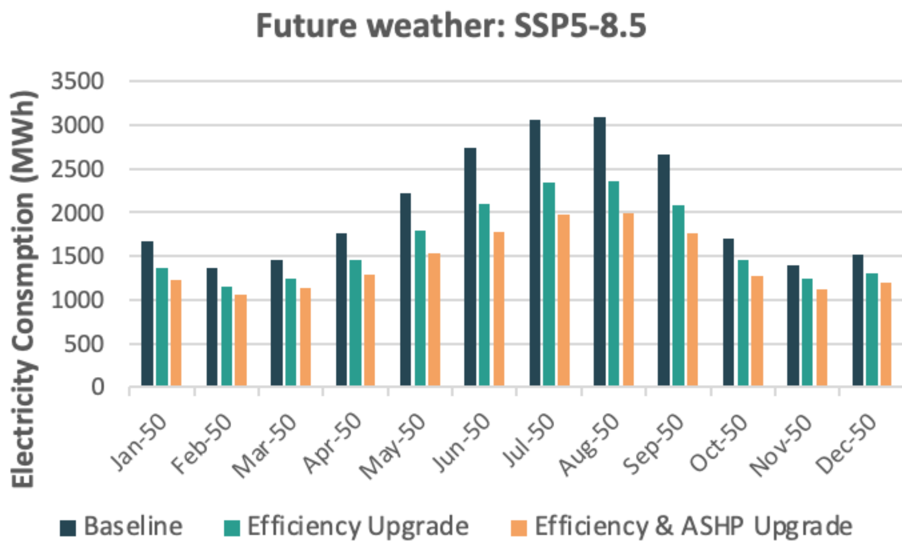

Figure 18: Figure showing the impact of efficiency upgrades alone and efficiency upgrades paired with heat pump upgrades utilizing future weather scenario SSP5-8.5 for a representative sample of residential buildings in ERCOT.

Hourly demand results

This section describes the final hourly demand profile results that were used as inputs into the grid modeling analysis. The residential results outlined in the previous section were combined with augmented commercial sector energy use profiles, district heating and cooling system impacts, and demand response methods to develop the 30 scenarios used to assess their impact on the evolution of the ERCOT grid. Table 5 shows some high-level statistics for each of the demand profiles generated and used in the grid modeling analysis.

Table 5: Table showing summary statistics for each of the hourly demand profiles utilized in the grid modeling analysis.

Scenario	Weather	2050 Peak Demand (GW)	Peak Day	2050 Annual Energy (TWh)
2018 Actual	*2018 Actual*	*73,287 (2018)*	*19-Jul*	*377 (2018)*
BASE	Today	144	19-Jul	799
BASE	SSP1-2.6	153	19-Jul	813
BASE	SSP2-4.5	158	6-Jan	837
BASE	SSP3-7.0	162	2-Aug	839
BASE	SSP5-8.5	149	6-Aug	820
EF	Today	125	19-Jul	703
EF	SSP1-2.6	129	19-Jul	717
EF	SSP2-4.5	132	28-Jul	732
EF	SSP3-7.0	134	2-Aug	731
EF	SSP5-8.5	128	21-Aug	720
EF + ASHP	Today	118	19-Jul	670
EF + ASHP	SSP1-2.6	120	19-Jul	677

EF + ASHP	SSP2-4.5	121	19-Jul	685
EF + ASHP	SSP3-7.0	122	2-Aug	686
EF + ASHP	SSP5-8.5	119	21-Aug	679
EF + ASHP + DHC	Today	118	23-Jul	671
EF + ASHP + DHC	SSP1-2.6	118	20-Jul	677
EF + ASHP + DHC	SSP2-4.5	121	28-Jul	686
EF + ASHP + DHC	SSP3-7.0	120	29-Jul	686
EF + ASHP + DHC	SSP5-8.5	118	29-Jul	679
EF + ASHP + COMM	Today	105	19-Jul	593
EF + ASHP + COMM	SSP1-2.6	107	19-Jul	592
EF + ASHP + COMM	SSP2-4.5	106	19-Jul	591
EF + ASHP + COMM	SSP3-7.0	107	2-Aug	593
EF + ASHP + COMM	SSP5-8.5	106	21-Aug	595
EF + ASHP + COMM + DR	Today	100	31-May	593
EF + ASHP + COMM + DR	SSP1-2.6	101	28-Jun	592
EF + ASHP + COMM + DR	SSP2-4.5	101	2-Jul	591
EF + ASHP + COMM + DR	SSP3-7.0	102	27-Jun	593
EF + ASHP + COMM + DR	SSP5-8.5	100	30-May	595

In Table 5, Scenario refers to the inclusion (or not) of various types of efficiency upgrades or other aspects considered where in the “Scenario” column BASE means no energy efficiency upgrades were considered, EF refers to residential energy efficiency upgrades[7], ASHP refers to the upgrading residential heating and cooling equipment upgrades[8], DCH refers to the switching of residential heating and cooling to district heating and cooling systems, COMM refers to the inclusion of similar energy efficiency upgrades to commercial buildings, and DR refers to the inclusion of demand response. Multiple values in the same row indicate that each of those augmentations were considered in that scenario.

In the “Weather” column, *Today* refers to the assumption that the weather and climate in 2050 will be like the weather and climate is now and SSP1-2.6 to SSP5-8.5 refer to future weather scenarios where 2050 is generally warmer than today (see Section: Estimated future weather conditions). The column “2050 Peak Demand” refers to the highest hourly demand value for that scenario in 2050 in giga-watts (GW), the column “Peak Day” refers to the day that the grid experienced peak demand in 2050 in that scenario, and the column “2050 Annual Energy” refers to the amount of electricity consumed by ERCOT in 2050 for each scenario in terawatt-hours (TWh).

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[7] Including increasing the insulation attic insulation levels to a minimum of R-38, upgrading windows to dual-pane Low-E units, decreasing outside air infiltration to 7 ACH50. See Section: Residential demand.
[8] Upgrading all existing HVAC units to SEER 18, 9.3 HSPF efficiency heat pumps.

In each scenario group (BASE, EF, EF + ASHP, etc.), more extreme future weather scenarios generally meant higher overall energy use and higher peak demand values. However, the energy efficiency measures deployed in this analysis acted as a buffer against higher levels of overall energy use and peak demand in the face of more extreme future temperatures. For example, in the BASE scenario case, energy use was up to 5% higher and peak demand about 4% higher in future weather scenarios compared to energy use with today's weather. However, in the case with the highest levels of efficiency and demand response (EF + ASHP + COMM + DR), the energy use and peak demand implications of more extreme future weather are much more muted, with energy use flat and peak demand increasing by only 1.6% relative to today's weather.

Compared to 2018 energy use and peak demand, the highest 2050 case of no energy efficiency measures and warmer weather increases energy use and peak demand by over 120%, whereas energy efficiency measures and demand response measures can limit energy use growth to less than 60% and peak demand growth to less than 40% in 2050 over 2018 values.

Grid modeling results

This section discusses the results of the grid modeling analyses that sought to assess the grid impacts of the various future weather and efficiency futures discussed above. Table 6 shows the high-level summaries of some of the key findings of the grid modeling studies.

Table 6: Table showing high-level results from the grid modeling analysis part of this study. Note that all values are for 2050 except the first row, which are the actual values for today (2018/2021) which are included for comparison.

Scenario	**Weather**	**Total Power Plant Capacity (GW, 2050)**	**Total Transmission Capacity (GW, 2050)**	**Energy Cost ($/MWh, 2050)**	**Carbon Intensity (kgCO_2/MWh, 2050)**
2018 Actual	*2018*	*100 (2018)*	*41 (2018)*	*35.63 (2018)*	*385*[9]
BASE	Today	226	103	24.99	80
BASE	SSP1-2.6	221	92	21.81	72
BASE	SSP2-4.5	232	101	22.21	93
BASE	SSP3-7.0	234	88	20.87	76
BASE	SSP5-8.5	221	90	23.27	74
EF	Today	188	90	18.93	44
EF	SSP1-2.6	189	93	19.32	45
EF	SSP2-4.5	196	102	20.22	51
EF	SSP3-7.0	196	95	19.84	46
EF	SSP5-8.5	191	93	19.14	45
EF + ASHP	Today	180	93	17.61	33
EF + ASHP	SSP1-2.6	177	91	18.2	37

[9] Based on 2021 data for Texas from Carnegie Melon University's Power Sector Carbon Index [82].

EF + ASHP	SSP2-4.5	182	98	15.46	38
EF + ASHP	SSP3-7.0	180	90	17.72	38
EF + ASHP	SSP5-8.5	177	92	16.66	37
EF + ASHP + DHC	Today	170	97	16.75	35
EF + ASHP + DHC	SSP1-2.6	172	92	18.41	35
EF + ASHP + DHC	SSP2-4.5	184	99	18.61	37
EF + ASHP + DHC	SSP3-7.0	174	96	16.79	35
EF + ASHP + DHC	SSP5-8.5	177	93	18.29	34
EF + ASHP + COMM	Today	157	81	16.79	27
EF + ASHP + COMM	SSP1-2.6	151	74	13.95	35
EF + ASHP + COMM	SSP2-4.5	155	84	15.34	30
EF + ASHP + COMM	SSP3-7.0	153	74	14.30	34
EF + ASHP + COMM	SSP5-8.5	153	78	13.16	34
EF + ASHP + COMM + DR	Today	157	81	14.38	27
EF + ASHP + COMM + DR	SSP1-2.6	151	74	13.95	35
EF + ASHP + COMM + DR	SSP2-4.5	155	84	15.57	30
EF + ASHP + COMM + DR	SSP3-7.0	153	74	14.29	34
EF + ASHP + COMM + DR	SSP5-8.5	153	78	13.42	34

Similar to Table 5, in Table 6, Scenario refers to the inclusion (or not) of various types of efficiency upgrades or other aspects considered where in the “Scenario” column BASE means no energy efficiency upgrades were considered, EF refers to residential energy efficiency upgrades[10], ASHP refers to the upgrading residential heating and cooling equipment upgrades[11], DCH refers to the switching of residential heating and cooling to district heating and cooling systems, COMM refers to the inclusion of similar energy efficiency upgrades to commercial buildings, and DR refers to the inclusion of demand response. Multiple values in the same row indicate that each of those augmentations were considered in that scenario.

In the “Weather” column in Table 6, Today refers to the assumption that the weather and climate in 2050 will be like the weather and climate is now and SSP1-2.6 to SSP5-8.5 refer to future weather scenarios where 2050 is generally warmer than today (see Section: Estimated future weather conditions). The column “Total Power Plant Capacity” refers to the sum total, in giga-watts (GW), of the power plant capacity on the ERCOT system in 2050 for that scenario/weather combination and the column “Total Transmission Capacity” refers to the total amount of transmission capacity, in GW, present on the system in 2050. The column “Energy Cost” refers to the average annual cost, in $/MWh, of wholesale electricity in the ERCOT market in 2050 and the column “Carbon Intensity” refers to the average annual carbon intensity (kg-CO_2/MWh) of electricity in the ERCOT grid in 2050 for that scenario/weather combination.

[10] Including increasing the insulation attic insulation levels to a minimum of R-38, upgrading windows to dual-pane Low-E units, decreasing outside air infiltration to 7 ACH50. See Section: Residential demand.
[11] Upgrading all existing HVAC units to SEER 18, 9.3 HSPF efficiency heat pumps.

Similarly to the hourly demand results, the grid modeling analyses indicated that more extreme future weather within each scenario group would, in general, require more total power plant and transmission line capacity than milder weather years. However, this pattern did not always hold within each scenario group and the effect was less pronounced than in the demand profiles. The types of power plants chosen by the model are not only based on the amount of energy needed, but also strongly impacted by *when* that energy is needed, known as the demand shape.

The shape of the demand can change based on the weather, i.e. more air-conditioning use on hotter afternoons, or by efficiency upgrades such as more insulation that shifts (lower) cooling needs to later in the day, or demand response measures that reduce demand during certain periods. Thus, if the shape of the demand curve shifts to better align with the output from solar or wind, the model is likely to choose more of that because they are often among the cheapest technologies to deploy. If the shape of the demand curve shifts away from such production profiles, the model might choose a more dispatchable technology, such as natural gas, even if it costs more per unit energy generated.

However, across a range of scenarios energy efficiency and demand response measures clearly reduced the need to build as many power plants by about 35% compared to the BASE scenario coupled with more extreme weather and transmission lines and by as much as about 27% compared to the BASE scenario coupled with more extreme weather.

The cost of electricity ($/MWh) and the carbon intensity of electricity (kg-CO_2/MWh) also generally decline in more efficient future scenarios. Figure 19 to Figure 22 show the total capacity and energy generation results for the ERCOT grid for the BASE scenario with SSP3-7.0 weather and the EF + ASHP + COMM + DR with SSP3-7.0 weather. The same figures for the rest of the scenario are available in Appendix A.

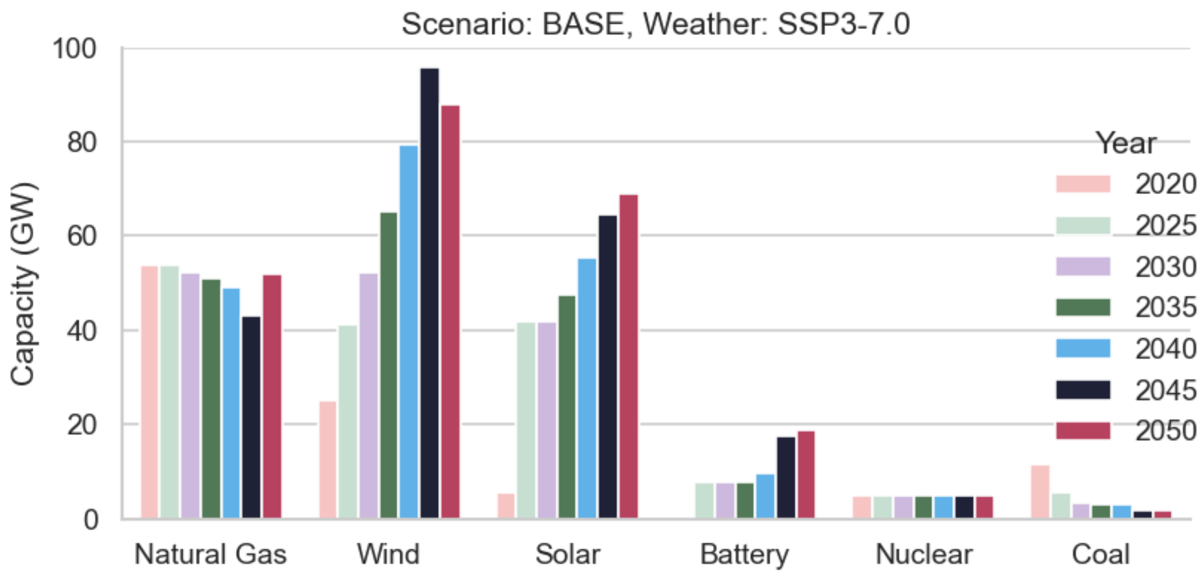

Figure 19: Figure showing the total capacity for various generation types in the ERCOT grid in the BASE scenario assuming SSP3-7.0 weather.

Figure 19 shows the change in each type of generation capacity in the BASE scenario with SSP3-7.0 weather for 2020 to 2050. Note that smaller generation types, such as biomass and oil, were not included given their relative smaller size. In general, the model builds more wind, solar, and battery systems in the earlier years, natural gas declines in the 2030s to mid 2040s before rebounding in 2050, nuclear stays constant at today's levels, and most coal retires by 2050. Also, by 2050, we see some wind farms beginning to retire and not all are replaced with just more wind. Note that power plants are retiring throughout the analysis period as they reach the end of their economic life and Figure 19 shows only total capacity of that type of plant in that year. For example, the capacity of natural gas combined cycle units increases from 2020 to 2050, but over the same time period, the model retires about 60% of the less efficient natural gas combustion turbine units. Figure 20 shows data for the same scenario, but instead shows the percentage of electricity generated by each fuel type from 2020 to 2050.

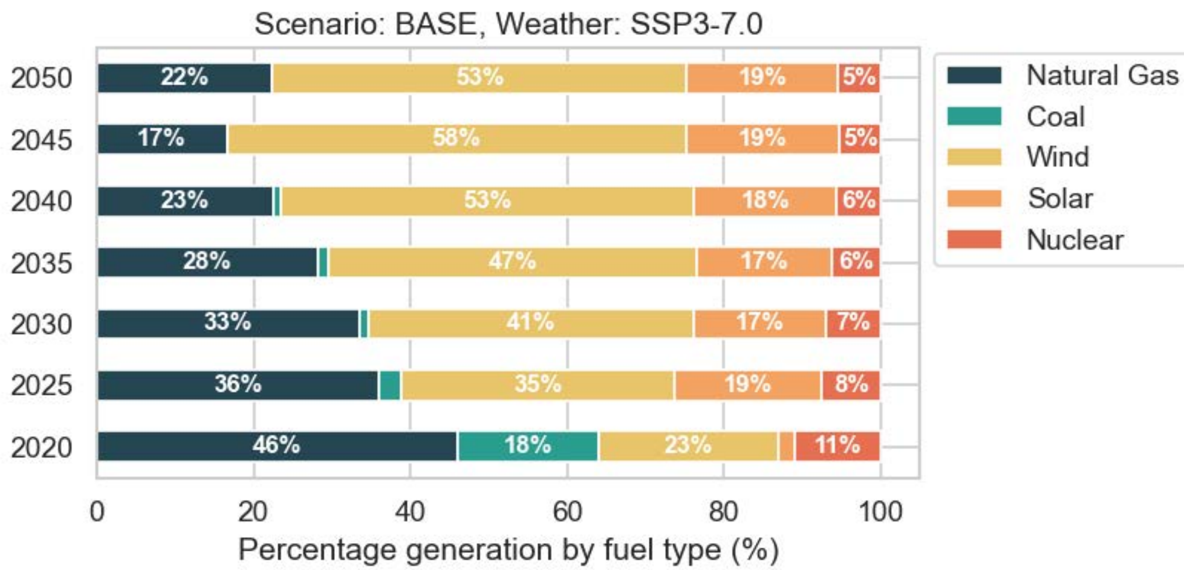

Figure 20: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the BASE scenario assuming SPP3-7.0 weather.

Figure 20 shows the change in the percentage of electricity generated by each major fuel type[12] from 2020 to 2050. Note that the amount of electricity being generated more than doubles from 2020 to 2050, in this scenario from about 377 TWh to 839 TWh, see Table 5. In this scenario, the model results indicate that the 2050 grid evolves to see about 53% of electricity generation come from wind, 22% from natural gas, 19% from solar, 5% from nuclear and the remining 1% from coal which is too small to see in the figure.

For comparison, Figure 21 and Figure 22 show the same data as above, assuming the same more extreme future weather but for the most efficient scenario considered (EF + ASHP + COMM + DR).

[12] Biomass and oil not shown for being < 0.01% of the total.

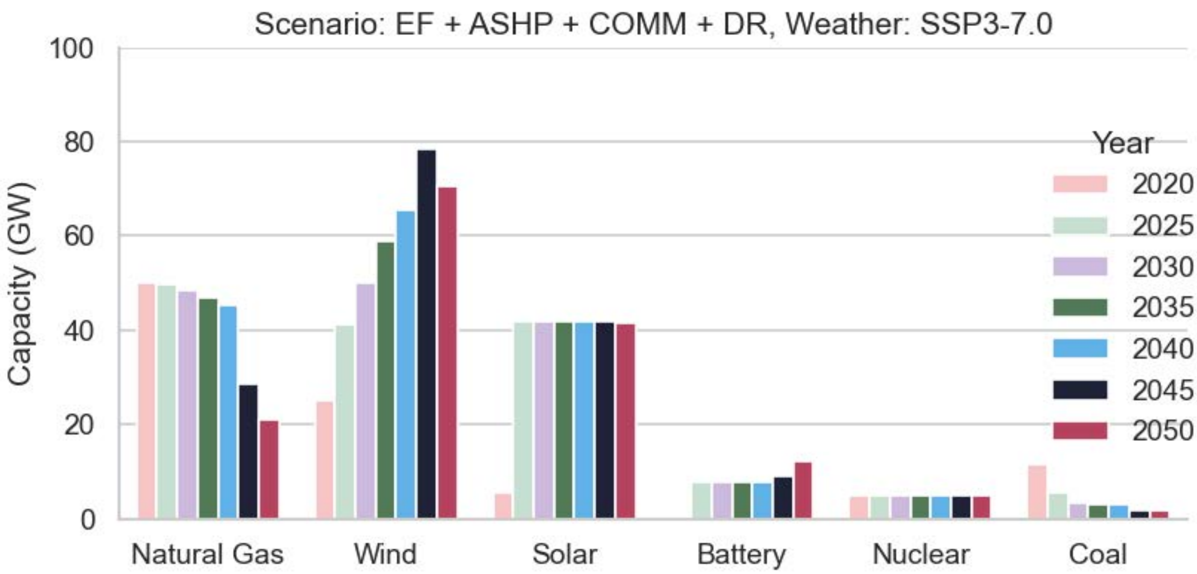

Figure 21: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM + DR scenario assuming SSP3-7.0 weather.

This more efficient scenario requires much less energy (593 TWh vs. 839 TWh) in 2050 and thus requires less overall power plant capacity (153 GW vs. 234 GW) to meet a more efficient future. In this scenario, solar grows quickly early before plateauing at about 40 GW, whereas wind continues to grow through 2045 before seeing some retirements take effect. Energy storage (battery) capacity grows quickly and then continues to grow in the 2040s. Total natural gas and coal capacity decline as other technologies take their place and nuclear capacity remains constant. Similar to the previous scenario, Figure 22 shows an increasing share of total electricity generated coming mostly from wind and solar.

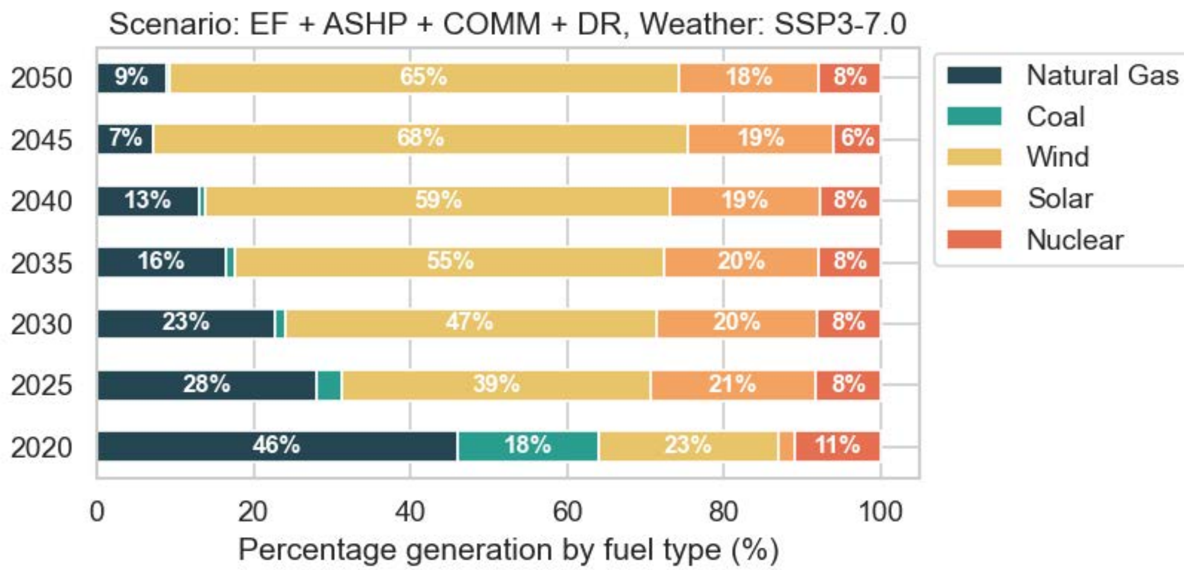

Figure 22: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM + DR scenario assuming SPP3-7.0 weather.

Figure 33Figure 92Figures showing the same results for each of the other scenarios are included in Appendix A.

Winter Storm Uri analysis

This section includes an independent look at the impact of events such as Winter Storm Uri on how the grid might evolve if it were designed to fully accommodate such an event. Even though the impacts of these types of events are massive the future weather analysis indicated that their future frequency could decline. The same grid modeling assumptions were used for this sub-analysis, with the exception of different assumptions about future demand. Essentially, the only difference between the following two scenarios is that the "normal" winter week of February 13-20, 2018[13] in the "no winter storm" case was taken out and the actual data from February 13-20, 2021 was used in its place. Figure 23 shows the capacity evolution of the electricity grid from 2020 to 2050 not considering a future storm such as Winter Storm Uri.

[13] 2018 was used as the base case year and scaled up to 2050 assuming 1.8% growth per year.

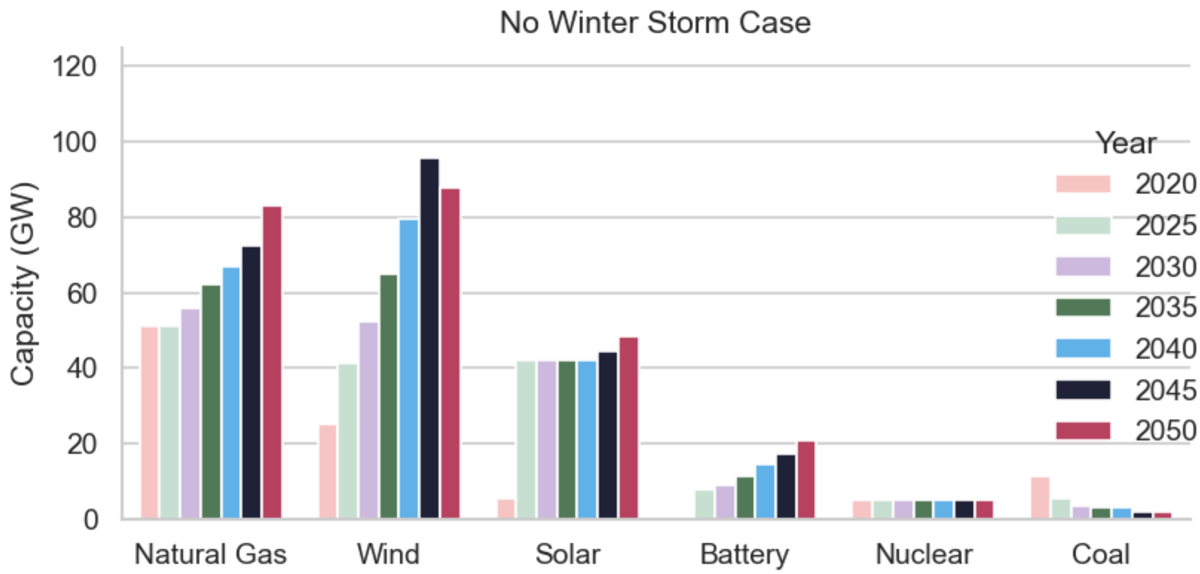

Figure 23: Figure showing the total capacity for various generation types in the ERCOT grid from 2020 to 2050 not considering a future winter storm on the same level as Winter Storm Uri.

Note that the results shown in Figure 23 are not directly comparable to other base cases in this analysis, such as that shown in Figure 33 as their respective future load profiles were calculated slightly differently. In this "no winter storm" base case, natural gas, solar, energy storage, and wind all generally increase with wind declining (retiring) on net in capacity after 2045, nuclear stays constant at today's levels and most coal retires. Figure 24 shows the energy generation by fuel type results for the same scenario.

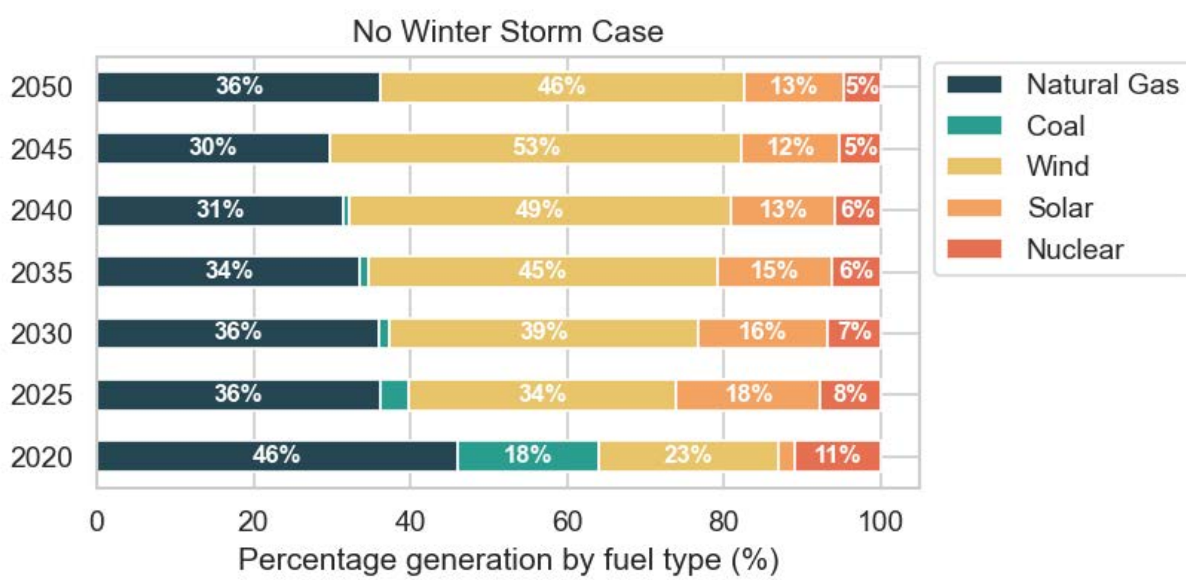

Figure 24: Figure showing the energy generation by fuel type in ERCOT from 2020 to 2050 not considering a future winter storm on the same level as Winter Storm Uri.

In this case, natural gas maintains about a third of the total amount of electricity generated in ERCOT from 2020 to 2050, with wind growing to about half. Figure 25 shows the total installed capacity of the ERCOT grid if we assume that a winter storm event such as Winter Storm Uri were to happen every year.

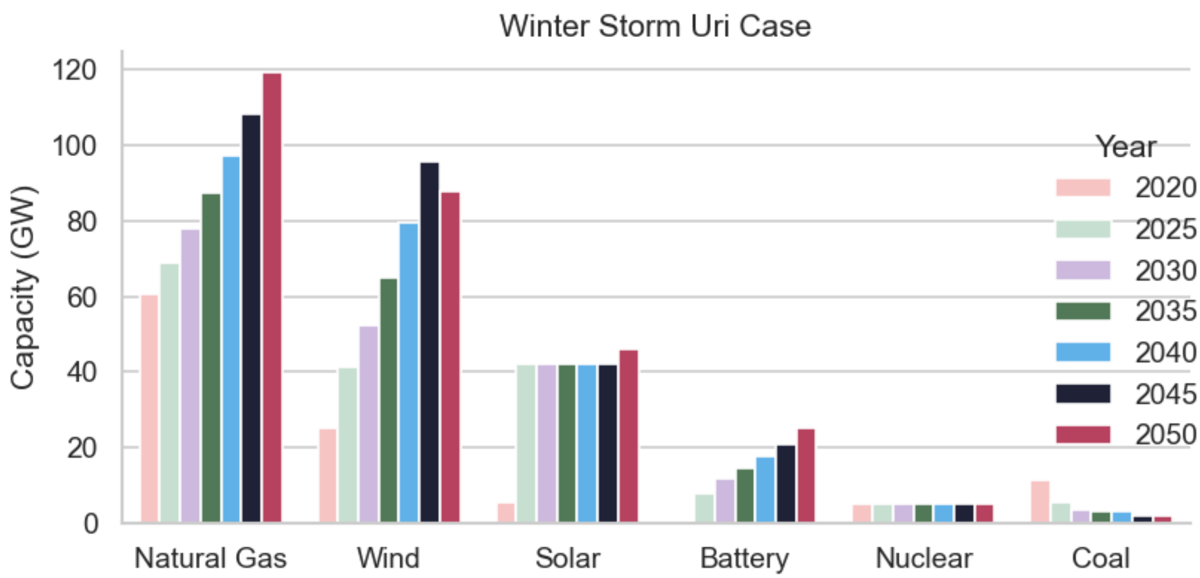

Figure 25: Figure showing the total capacity for various generation types in the ERCOT grid from 2020 to 2050 assuming that a future winter storm on the same level as Winter Storm Uri happens regularly.

The major difference between the winter storm and non-winter storm case is the amount of natural gas generation capacity deployed in the former case with the winter storm case deploying about 40 GW more natural gas capacity by 2050 than the non-winter storm case. Overall, the winter storm case required about 15% more power plant capacity by 2050 than the non-winter storm case (285 GW vs. 247 GW) Note that the model used did not take into account the loss of power plants or fuel due to weather conditions that, in February 2021, resulted in roughly half of the ERCOT power plant fleet being offline [27] [28]. However, except for about 5 GW more battery storage in the winter storm case, the other capacity types stayed roughly similar. In fact, Figure 26 shows that the energy generation by fuel type in the winter storm case are almost identical to that in the non-winter storm case.

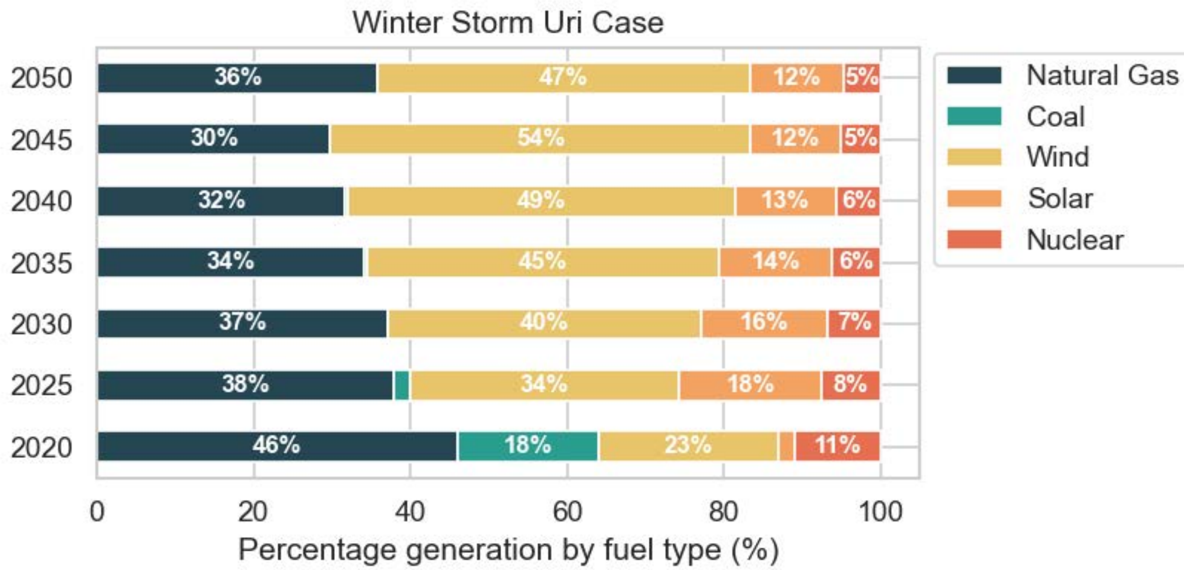

Figure 26: Figure showing the energy generation by fuel type in ERCOT from 2020 to 2050 considering a future winter storm on the same level as Winter Storm Uri happens regularly.

While not a part of this analysis, previous work has shown that more efficient buildings are able to withstand the loss of electricity for longer periods while maintaining more safe living temperatures [29]. The above analysis and these results indicate that energy efficiency retrofits and more stringent building codes can not only save energy and reduce costs, but also keep buildings livable in future situations when electricity is no longer available to power air-conditioning and heating systems.

All the data that support and underlie each of the modeling scenario results are available for download from the Texas Data Repository[14].

Building codes and energy efficiency programs

The installation and deployment of energy efficiency technologies and demand response tools are presently incentivized or required through building codes or energy efficiency programs. Because of the overlap between energy efficiency and making homes more resilient to power outages, many of these programs can provide Texas residents with an avenue to improve the energy efficiency and resilience of their homes.

Texas has adopted the 2015 International Energy Conservation Code (IECC) and American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) 90.1-2013 for commercial buildings. The state adopted the 2015 IECC residential code with amendments for residential buildings [30]. Both were effective as of 2016, moving the state from 2009 IECC residential and 2010 ASHRAE commercial standards to the 2015 updates [30]. The state enforces codes on state-owned or -funded buildings. Local code enforcement applies to other buildings [30].

[14] https://dataverse.tdl.org/dataverse/EEandResilience

Many local communities have adopted earlier building codes. For example, some communities have adopted 2009 IECC codes. While the 2006 codes use heat pumps as the baseline efficient technology, the Department of Energy has asserted that the 2009 codes are not clear in this respect [31]. The 2012 IECC code was updated and clarified to further outline the benefit of heat pumps over electric resistance heating, essentially penalizing electric resistance heating [31]. Homes with electric with the latter would have a harder time complying with subsequent building code updates compared to those with heat pumps. Communities with 2009 codes are potentially encouraging less efficient heating in new buildings.

Weatherization and energy efficiency programs reach an additional subset of buildings, residences of low-income individuals. The Texas weatherization program is administered by the Texas Department of Housing and Community Affairs (TDHCA) with funding from the Department of Energy's Weatherization Assistance Program (WAP) and the Department of Housing and Urban Development's Low-Income Home Energy Assistance Program (LIHEAP). Additional funding might be supplied by the energy utility. Weatherization subgrantees receiving money from TDHCA conduct diagnostic assessments to determine the upgrades needed for homes to address energy use, health, and safety. Using these assessments, they make prescribed updates to homes including attic, wall, floor, and pipe insulation; ASHRAE compliant exhaust fans; smoke and carbon monoxide detectors; air sealing; duct sealing; new refrigerators and water heaters; air conditioning and heating tune-up or replacement; solar screens; and improved windows. Low-cost measures such as low-flow shower heads and aerators, LED bulbs, weather-stripping, and water heater tank wraps, are also included. Minor gas leak repairs might be conducted if needed. In some areas, homes need all of the upgrades prescribed in the weatherization program. In others, some upgrades do not meet the savings to investment ratio determined by the National Energy Audit Tool after the initial audit. Program officers identified attic and wall insulation as well as sealing air infiltration as commonly needed upgrades. New roofs are the most needed revision but WAP and LIHEAP funding cannot be used for this service. In 2020, 2,615 dwellings in Texas were served through these programs [32].

The building codes apply to new construction and additions, meaning, while building codes can be impactful, they can only reach a subset of buildings. Weatherization programs can serve low-income individuals but, due to capacity constraints, reach fewer than 3,000 households per year in Texas. Additionally, renters are less likely to benefit as the landlord must allow upgrades to the property. Thus, many low-income individuals miss out on the building energy, health, and safety upgrades. Neither building codes nor weatherization reaches the remainder of existing homes.

Housing codes do apply to existing dwellings; however, they are often reactively rather than proactively enforced, to prioritize violations over inspections. For tenants, this type of enforcement means they must report a violation. Many might be unaware of the process, and marginalized tenants might be reticent to do so even if they are aware [33].

More detailed information about the energy efficiency programs offered by energy utilities in Texas and the types of services and customers these programs provide is given in Appendix B .

Survey of Energy Utility Professionals' Perspectives of Resilience in Energy Efficiency Programs

As part of this project and to gain a better standing of the current utility environment and barriers to deployment of further energy efficiency and resilience technologies, HARC and Frontier Energy conducted a survey of utility professionals regarding utility energy efficiency programs, home energy resilience, and regulations and policy.

Survey responses indicated that legislative, regulatory, and program changes are needed to implement resilience measures under utility energy efficiency programs and that current regulatory and program standards limit the inclusion of more resilience measures. Insulation, including ceiling, wall, and piping, are the most recommended and most prioritized under current program guidelines to improve the resilience of a home. Full survey results are provided in Appendix C .

Conclusions and Recommendations

Increasing electricity demand and future extreme weather events will put strain on the Texas electric grid. Historic events have shown the devastating impacts of grid outages and the need for resiliency planning and preparation for the future. Energy efficiency and demand response technologies can play a significant role in reducing future energy needs and peak demand and improve resiliency.

Several analyses were conducted to assess the impact of energy efficiency and demand response in Texas over several future weather scenarios, including baseline and three climate scenarios of differing severity. Hourly weather profiles for these future scenarios were developed to support building energy and grid modeling. The impacts of several energy efficiency and demand response measures, including residential and commercial energy efficiency, air source heat pumps, district heating and cooling, and demand response were included in the analyses.

Results from the residential building modeling show energy efficiency significantly reduces future building energy demands, even in more extreme climate scenarios. Because residential electricity consumption is responsible for about half of peak power demand in the winter and summer in Texas, residential energy efficiency and demand response programs are a uniquely large opportunity.

- Relative to a baseline of no energy efficiency upgrades, energy efficiency measures significantly reduced energy use by an average of about 20% across today's weather and all future weather scenarios.

- Relative to a baseline of no energy efficiency upgrades, installing energy efficiency upgrades and heat pumps in residential buildings in Texas uses about 30% less energy in 2050.
- Compared to 2018 energy use and peak demand, the highest 2050 case of no energy efficiency measures and warmer weather increases energy use and peak demand by over 120%, whereas energy efficiency measures and demand response measures can limit energy use growth to less than 60% and peak demand growth to less than 40% in 2050 over 2018 values.

Results from the grid modeling show that implementing demand response and energy efficiency measures decrease total electricity consumption and peak demand, even in extreme future weather scenarios.

- Energy efficiency and demand response measures reduced the need to build as many power plants by about 35% compared to the baseline scenario coupled with more extreme weather.
- Energy efficiency and demand response measures reduced the need to build transmission lines by as much as about 27% compared to the baseline scenario coupled with more extreme weather.
- The most efficient scenario (EF + ASHP + COMM + DR) requires much less energy (593 TWh vs. 839 TWh) in 2050 compared to a no efficiency measures alternative under the future weather conditions.

To complement the analyses and provide information on the mechanisms to deploy energy efficiency and demand response tools, we did a review of existing programs and a survey of existing utilities. While there are some existing programs at the state and federal level that work to implement energy efficiency and demand response, there is significant opportunity and need to expand and revise these programs and associated regulations to fully realize the significant energy savings and resiliency potential of energy efficiency and demand response.

Energy Assurance Plan Recommendations

Based on this study, the team has developed recommendations for updating the Energy Assuredness Plan sections, outlined in brief below and shown in italics.

Recommendation: Include various hazard risks listed by NOAA via disaster risk maps[15]

Texas experiences a variety of hazards. According to NOAA's assessment of billion-dollar disasters, Texas has experienced up to $50B in damages from drought, over $200B in damages from tropical cyclones, up to $20B in damages from flooding, up to $5B in damages from wildfire, up to $1B in damages from freeze and $50B from winter storm, and up to $100B in damages from severe storms. Severe weather events often damage energy infrastructure, limiting energy supplies across the state. Some areas of the state experience certain disasters with greater frequency. It is important to plan for potential risks, understanding both frequency and severity.

[15] https://www.ncei.noaa.gov/access/monitoring/billions/mapping

Recommendation: Add hydrogen.

Hydrogen is used for fertilizers and in the chemical and liquid fuels industries on the Gulf Coast. It can be stored directly or in carrier form (such as ammonia, methanol, or formic acid). Because hydrogen can be stored and used as fuel, it can also be used as fuel in heavy-duty vehicles and other forms of transportation as well as in power applications using turbines and fuel cell technologies [34]. *There are already plans to use hydrogen, blended with natural gas, to generate electricity in gas turbines* [35].

Hydrogen's point of use greenhouse emissions profile is minimal, and its lifecycle carbon intensity depends on how it is produced. When produced through electrolysis with renewable electricity, such as wind or solar, an electrochemical reaction splits water into hydrogen and oxygen without emitting carbon dioxide. Hydrogen can be produced with fossil fuels through steam reforming, gasification, or methane pyrolysis. To lower the carbon intensity, greenhouse gas emissions can be trapped and stored through carbon capture and storage (CCS). Because it is possible to produce carbon-neutral hydrogen, using gas turbine assets for power generation with hydrogen could be near-zero emissions.

Hydrogen use in power generation could support reliability and resiliency on the grid as a firm power generation source, supporting intermittent renewable power generation. Moreover, hydrogen can be produced and stored as a mode of flexible demand or demand response when there is excess electricity. Production can then be halted when electricity is scarce.

National net-zero models show increased use of hydrogen in medium- and heavy-duty trucks and in blends with natural gas in power generation. For example, Princeton's Net Zero America shows blends of 60-100% hydrogen or synthetic gas in gas turbines by 2050 while Williams et al. employs <10% blends of hydrogen in most of the scenarios modeled. Hydrogen provides reliability on the grid as a flexible demand. It is produced with excess renewable electricity and stored for future use, particularly in scenarios with high renewable penetration allowing for productive use of renewable electricity rather than curtailment. Furthermore, if hydrogen is adopted to help decarbonize hard to abate sectors such as transportation and industry.

Recommendation: This mandate has been achieved. This section could be removed.

Recommendation: Split solar and geothermal into their own sections. In this section, add a review of distributed generation technologies that may be more relevant in Texas in the future.

- *Solar*

Solar panels absorb and use a portion of the sun's light to provide heat or electricity. Texas, particularly West Texas, is an ideal location for solar due to high solar irradiance.

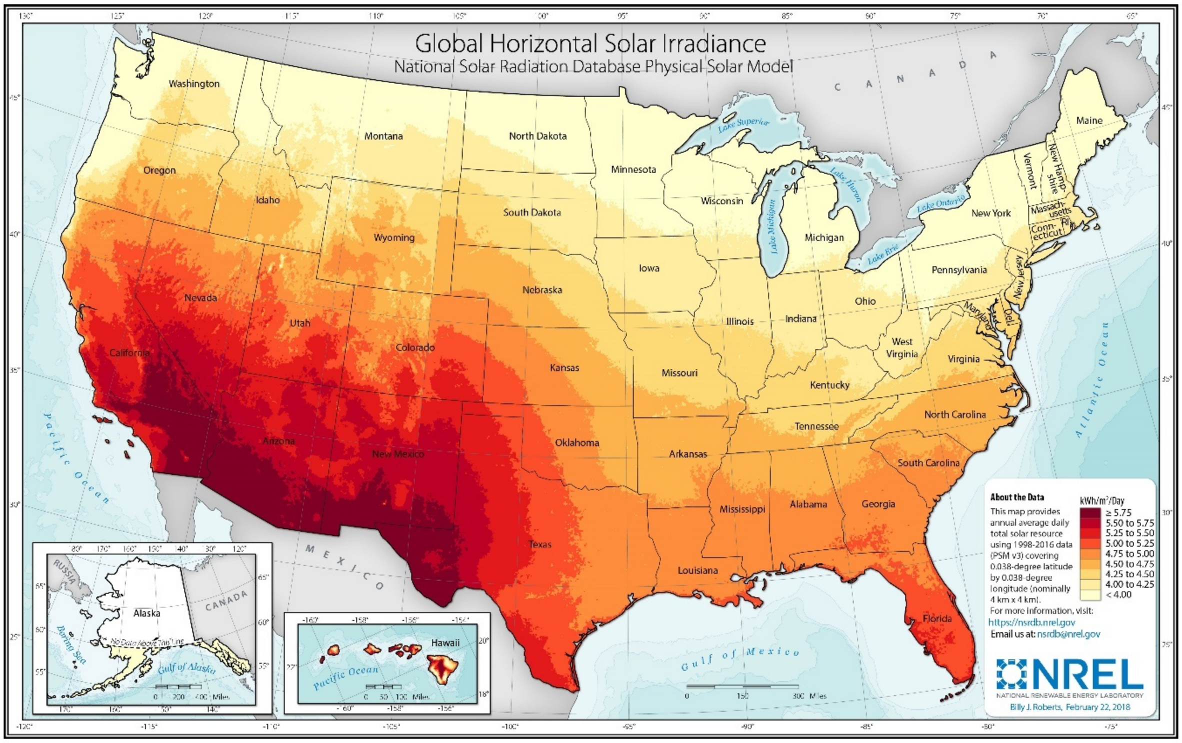

Figure 27: Figure showing daily average solar radiation (global horizontal) values across the US [36].

Solar can be used on the rooftops of homes and businesses or at the larger utility-scale to be sold to anyone buying power from the electricity grid. With community solar, individuals or groups share ownership of and use power generated by a local solar farm. For example, MP2 and Local Sun provide community solar from Sealy, TX through a retail electric plan.

Solar power is only available when the sun is shining and does not provide conventional system inertia to the power grid.[16] *Using a battery with solar power pairs the benefits of both resources—a battery could use solar panels to charge during the day and discharge at night when the sun is no longer shining. Similarly, other firm resources can provide reliability to the grid or, on a smaller scale, to a microgrid when solar power is not available. With higher*

[16] Pilot demonstrations have shown the ability to provide some synthetic inertia to help maintain the reliability of the grid [88] [89].

penetrations of solar, the grid will need to be designed with ancillary services for reliability, flexibility, inertia, and energy storage.

Net zero studies such as the White House's "The Long-Term Strategy of the United States," Williams et al., Vibrant Clean Energy's Zero by Fifty, Princeton's Net Zero America, Electric Power Research Institute's "Powering Decarbonization: Strategies for Net-Zero CO2 Emissions," and Berkeley 2035 model heavy reliance on solar power to 2050. Depending on the study or scenario, wind and solar power together supply between 43-91% of electricity generation due to major installations and generation increases. To reach this level of penetration, wind and solar capacity must rapidly increase between now and 2035. Factors such as land use, high renewable energy prices, or low natural gas prices constrain growth of wind and solar. When land use is constrained, residential photovoltaic (PV) solar generation increases faster but concentrated solar power (CSP) does not increase in any major net zero study. To maintain reliability, some net zero studies rely on flexible demands. For example, excess solar and wind resources are used to generate hydrogen via electrolysis for long-term energy storage. Other flexible demands include direct air capture and electric boilers. More transmission, including interconnection across grids, is needed to connect solar and wind resources to demand centers. Princeton Net Zero America estimates a need for a ~60% increase in transmission by 2030 that will then triple by 2050.

Residents who choose their own electricity provider can switch to a plan that uses 100% renewable energy. Shop on Texas's official site: PowerToChoose.com. Use the filter "Renewable Energy" to choose "100% Renewable" and refresh your results. Find out if rooftop PV solar would be a good fit for your home at solartexas.harcresearch.org.

- *Geothermal*

Geothermal employs heat from below the earth's surface for energy. It is a source for firm renewable energy because heat is continuously produced. Geothermal is classified for three uses: direct use and district heating, electricity generation, and heat pumps.

Direct use and district heating use naturally occurring springs and reservoirs near the earth's surface to provide for bathing, cooking, and heating. This method is common in areas with naturally occurring hot water near the earth's surface, such as Iceland.

Geothermal electricity generation uses hot water or steam from deep below the earth's surface, accessed via drilling steam or hot water wells. Because hydrothermal resources can be accessed on demand, these geothermal resources can be a firm, dispatchable power source for electricity. Using a firm renewable energy source to augment other intermittent renewable energy provides reliability to the grid without producing additional greenhouse gases. Geothermal power plants in the U.S. are located near hydrothermal reservoirs in western states. Texas has modest hydrothermal resources for electricity as shown in the figure below.

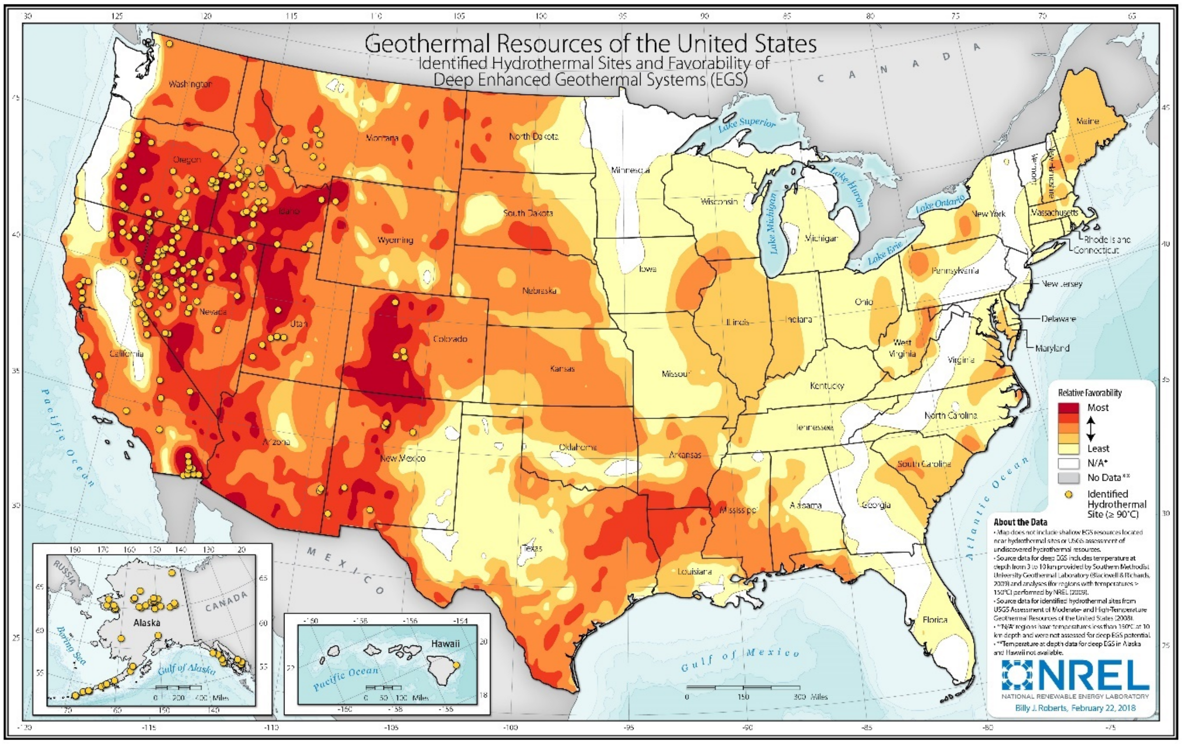

Figure 28: Figure showing hydrothermal resources across the US [37].

Net zero studies have estimated modest growth in geothermal electricity generation. For example, Vibrant Clean Energy's Zero by Fifty and Princeton's Net Zero America both emphasize the importance of continuing to invest in advanced geothermal to be able to use this technology in the future, lowering its projected cost and potential for earlier installation.

Additionally, residential and commercial buildings can take advantage of geothermal resources through ground source heat pumps taking advantage of the constant natural temperature of the earth's surface. These heat pumps are an efficient renewable energy technology that uses the earth to maintain a constant temperature year-round, transferring naturally existing heat from the ground to the surface in winter and to the ground in summer rather than combusting fuels. Net zero studies estimate modest use of geothermal heat pumps in both residential and commercial buildings by 2050.

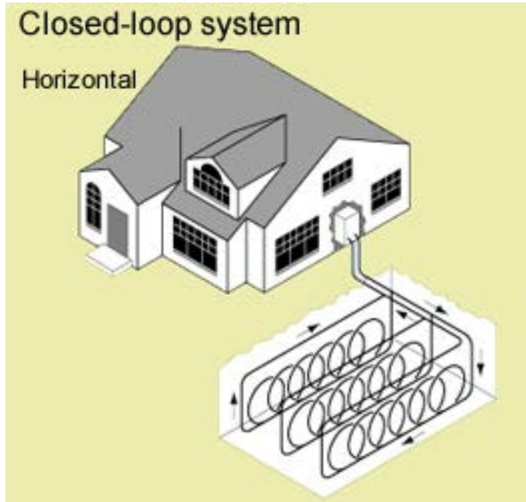

Figure 29: FIgure showing the layout of a closed-loop geothermal heating and cooling system [38].

- *Nuclear – SMR, MSR*

Molten salt reactors (MSRs) use molten salts as a coolant, specifically fluoride salt [39]. *Nuclear fuels such as thorium, uranium, and plutonium dissolve into the molten fluoride and can be easily separated from one another. Because fuels are liquid, solid fuel is not required, eliminating the need to dispose of the fuel. MSRs generate high-temperature heat that can be used for electricity or process heat applications. MSRs date back to the 1960s.*

Small Modular Reactors (SMRs) are advanced distributed nuclear reactors with small footprints, meaning they have reduced capital costs and easier siting compared to traditional nuclear plants [40]. *Reactors might vary in size from tens to hundreds of megawatts and can be used for power generation, process heat, or other applications.*

In its net zero by 2050 study, Vibrant Clean Energy employs MSR and SMR technology in technologically advanced scenarios, assuming the technologies will mature to a point where they can be used at scale. Other net zero studies rely on nuclear, generally but indicate that it is important to continue to invest in these advanced technologies to make progress in maturation, scale, cost, and performance.

Storage Technologies 78

New Energy Issues 85

> ***Recommendation: Split demand response (mentioned in Smart Grid, Economic Variables, and Resource Adequacy) into its own section and include potential in each major sector, such as EV charging, space conditioning, and water heating.***

Demand response is a way for electricity users to participate in the grid and assist with reliability by reducing electricity use during peak periods or shifting it to non-peak times [41]. *Demand response programs use financial incentives like time-of-use rates to encourage these reductions or demand shifts. In Texas, industrial users participate in demand response programs. However,* *commercial or residential users can also participate in demand response. Some utilities use smart thermostats or other smart devices to achieve peak demand reductions in commercial and residential buildings.*

In the future, net zero studies estimate that flexible demands that can respond to supply constraints will be integral to maintaining grid reliability, specifically because of the increased use of variable renewable energy resources like wind and solar. When demands can respond flexibly, they can match the electricity sources with more intermittent supplies. Additionally, they can respond to locational supply constraints such as transmission congestion that could limit electricity supplies reaching demands. Flexible demands could also increase their use when electricity supply exceeds demand. Flexible demands included in Princeton's Net Zero America and Williams et al. include electrolysis, electric boilers, direct air capture, and storage. Additional residential, commercial, and transportation demands include smart charging for electric vehicles and automating heat pumps and water heating.

Recommendation: Add benefit of building weatherization including floor, ceiling, wall, attic insulation; insulating pipes; weatherstripping alongside energy efficiency measures.

Weatherization can improve the ability of buildings to provide safe shelter year-round but especially during extreme temperatures, power outages, and especially during power outages that occur at extreme temperatures. Properly weatherizing a building with improvements such as floor, ceiling, wall, attic insulation; insulating pipes; weatherstripping alongside energy efficiency measures can reduce the electricity needed to keep a building safe when there is power and maintain safe temperatures if the power goes out. However, many Texas homes are not properly weatherized, meaning the building envelope releases heat to the environment in winter or allows heat inside in summer. Overcompensating for this leakiness by increasing heating or cooling leads to energy waste and high energy bills. If buildings lose power, they quickly become uncomfortable and eventually unsafe.

Typical weatherization changes might include:

- *Adding floor, ceiling, wall, attic, and pipe insulation,*
- *Upgrading windows and doors for efficiency,*
- *Sealing air leaks,*
- *Updating the heating and air conditioning system, and*
- *Energy efficiency upgrades*

Weatherization programs target residences of low-income individuals. The Texas weatherization program is administered by the Texas Department of Housing and Community Affairs with funding from the Department of Energy's Weatherization Assistance Program and the Department of Housing and Urban Development's Low-Income Home Energy Assistance Program. Additional funding might be supplied by the energy utility.

Residents who do not qualify for weatherization can make their own changes by beginning with a home energy audit. A professional home energy audit will analyze previous energy bills; inspect for insulation, hazards, and air or water leaks; evaluate health and safety concerns; and develop a home energy report. Residents can conduct their own home energy audit using the U.S. DOE Do-It-Yourself guide.

Smart Grid 85

Recommendation: Update to 2022 smart technologies and use of Smart Meter Texas, as well as use of smart technologies for grid resilience

Smart Meter Texas is a website endorsed by The Public Utility Commission of Texas in which customers served by the competitive electricity market can access and review their electricity use data. Understanding your electricity use can help residents better manage it and save energy and money at home. The following graphic shows how to sign up for Smart Meter Texas.

To create an account, ***use the name that appears on your electric bill*** and the information from **a recent electricity bill** for your current address.

1. Visit **www.smartmetertexas.com/register**
2. Select Account Type: **residential**
3. Enter the **name on your bill** and **email address**
4. Looking at your most recent electricity bill, identify your
   a. **ESIID** (or ESID)
   b. **Meter number**, and
   c. **Retail Electric Provider's Name**
5. Create a **User ID**
6. Agree to the **Terms and Conditions**
7. Click **Sign Up**
8. Check your email to complete the registration process and set up a password

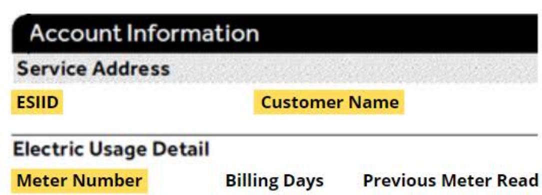

Figure 30: Figure showing the process for signing up for Smart Meter Texas.

Cyber Security 100

Plug-In Hybrid Electric Vehicles 126

Recommendation: remove this section and replace with electric vehicles

Approximately 134,000 electric vehicles (EVs) were registered in Texas by mid-2022, about 1% of vehicles registered in Texas [42]. *About 74% were battery electric (BEV), and 26% were plug-in hybrid EVs. Travis County leads vehicle registrations, as shown in the figure below. Some utilities such as CPS Energy, Austin Energy, Entergy, Southwestern Electric Power Company, and Denton Municipal Electric have rebate programs for EVs. Since 2020, the number of EVs has almost* *tripled, and, by 2028, ERCOT estimates there will be about 1 million EVs in Texas. In Q3 of 2021, EVs reached about 10.8% of global sales at 1.7 million units sold* [43]*. The EV market in the U.S. has been dominated by Tesla, including about 79% of EV sales in 2020* [44]*, and most EVs registered in Texas were manufactured by Tesla.*

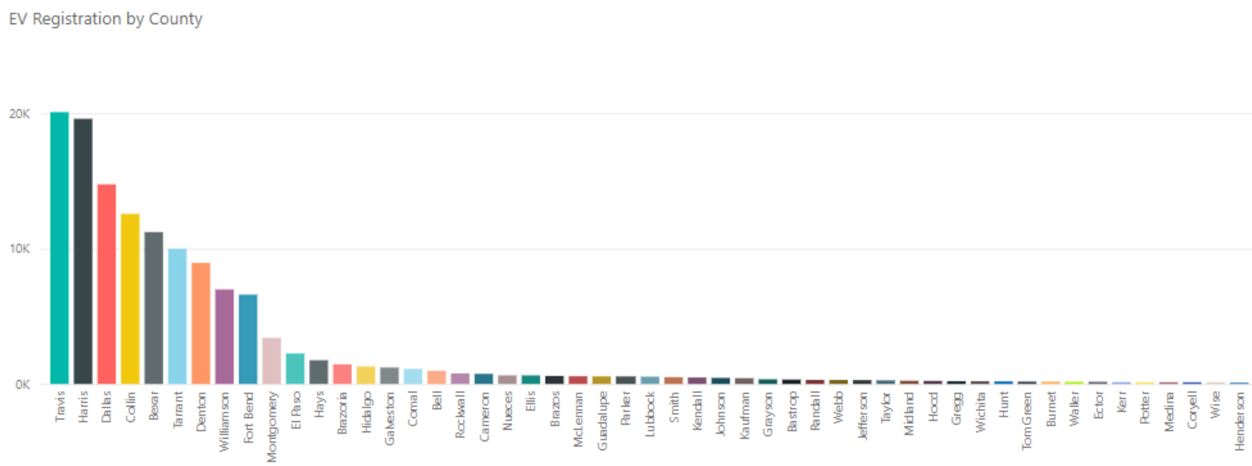

Figure 31: Figures showing electric vehicle registrations by county [45].

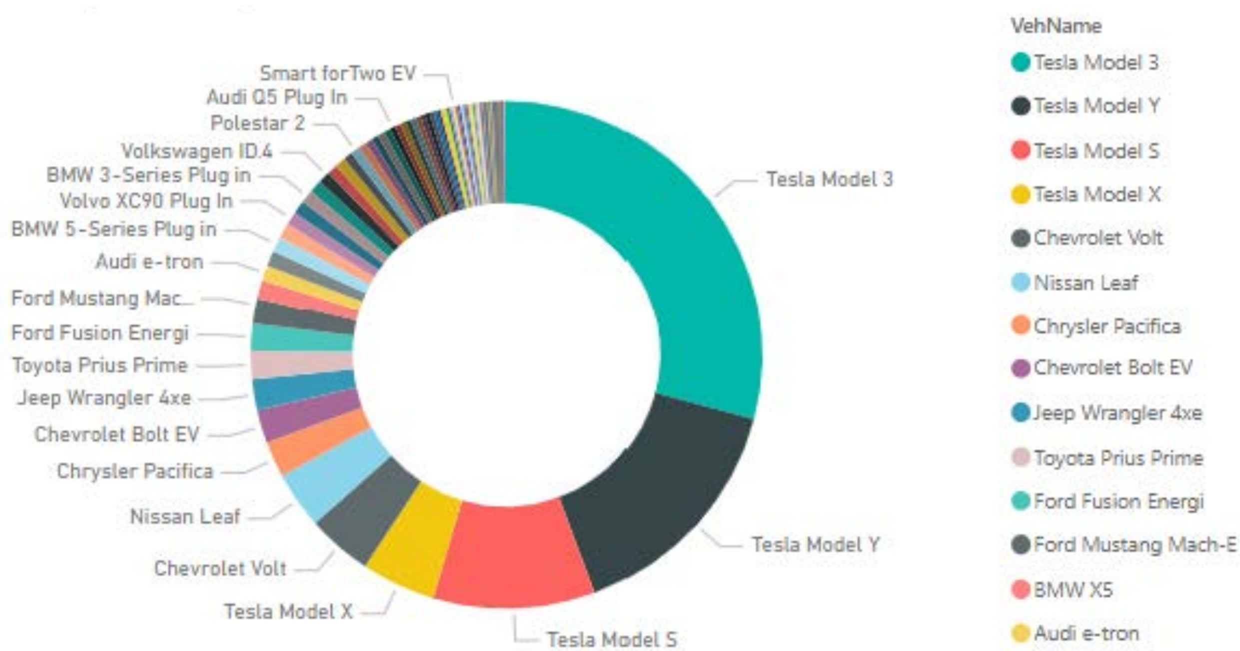

Figure 32: Figure showing electric vehicles registered in Texas by manufacturer and model [45].

In a survey of electric vehicle perceptions, most respondents indicated prices and lack of charging stations as hurdles for EV adoption [46]*. There are over 2,300 DC level 2 fast charging stations in Texas with over 5,600 electric vehicle supply equipment (EVSE) ports as of August 2022* [47]*.*

Net zero studies, Princeton Net Zero America and Williams et al., model a heavy reliance on EVs across all vehicle types. In high electrification scenarios, BEVs comprise 100% of light-duty vehicle sales between 2040 and 2050, reaching 90-97% of total stock by 2050. Charging infrastructure also rapidly expands alongside sales. In delayed electrification scenarios, BEVs comprise 85-90% of sales by 2050.

Energy Efficiency 130

Recommendation: update with recommended technologies, e.g. net-zero strategies such as more efficient building envelopes as well as space and water heating equipment.

Net zero studies, Princeton's Net Zero America and Williams et al., model electrification of end uses across sectors as a method of decarbonization and energy efficiency. In the transportation sector, battery electric vehicles dominate light-duty vehicles by 2050 while BEVs and hydrogen vehicles dominate medium- and heavy-duty vehicle stock by 2050. In the residential and commercial sector, electrification strategies include heat pumps for space and water heating and electric devices cooking. Heat pumps sales increase to 100% between 2030 and 2040 in both Princeton's Net Zero America and Williams et al., reaching 95-100% of stock by 2050.

In response to Winter Storm Uri, the American Council for an Energy Efficient Economy evaluated strategies that could increase Texas's energy efficiency, reducing total electricity demand. ACEEE recommends that Texas utilities enact seven programs to achieve large peak demand savings in both summer and winter:

- *Program to replace electric furnaces with ENERGY STAR heat pumps*
- *Attic insulation and sealing incentive program*
- *Smart thermostat incentive program*
- *Heat pump water heaters incentive program*
- *Central air conditioner demand response program with smart thermostat control*
- *Water heater demand response program*
- *Electric vehicle managed charging program*

Recommendation: Put Texas in context of other states' energy efficiency policy and efforts.

In 2011, Texas adopted SB 1125, the first statewide energy efficiency goal in the U.S., requiring utilities to save 0.4% of each company's peak demand. However, the standard has not been updated since and, in 2018, net savings was 0.19% compared to the average 0.75% of electricity retail sales [48]*. The ACEEE 2020 State Energy Efficiency Scorecard ranks Texas as 38th in energy efficiency savings and 36th in energy efficiency spending as a percent of utility revenues* [48].

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Recommendation: include interconnectedness of electricity and gas

As per recommendations from FERC (the Federal Energy Regulatory Commission) and PUCT (Public Utilities Commission of Texas), analyzing the interdependencies of power and gas would be valuable for reliability. These interdependencies include the ways by which the gas system depends on electricity (for compressors, separations, liquids management, anti-freeze equipment, etc.) and the ways by which the power sector depends on gas (for boilers, gas turbines, combined cycle systems, and reciprocating engines). Identifying these connections to prevent cascading failures is a key recommendation from FERC as well as other grid experts after winter storm events in 1989, 2011 and 2021. In particular, freeze-offs in the gas system in winter events caused derates or loss of capacity at gas-fueled power plants and FERC recommends winterizing the gas system. In addition, power outages (because of errors or because gas operators signed up for interruptible power supply) disabled operation of the gas system. Winterizing the power sector, prohibiting critical gas infrastructure from signing up for interruptible power supply contracts, identifying circuits that include critical gas infrastructure, and winterizing the gas system are all assurance steps worthy of inclusion.

Acknowledgements

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Appendix A

This appendix includes more figures from each of the scenarios in the grid modeling analysis.

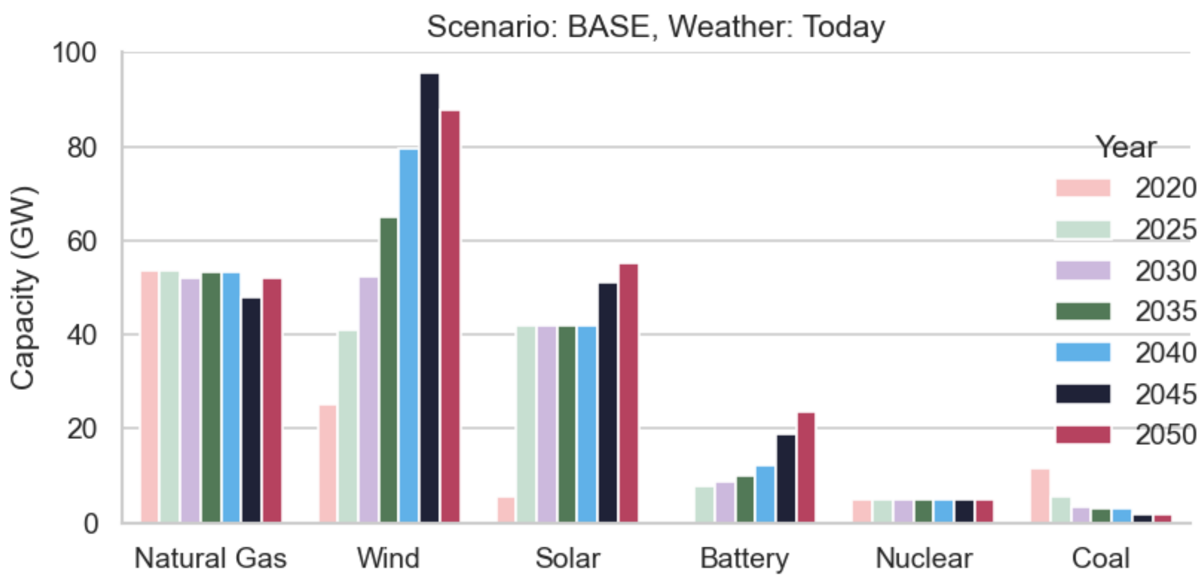


Figure 33: Figure showing the total capacity for various generation types in the ERCOT grid in the BASE scenario assuming Today's weather.

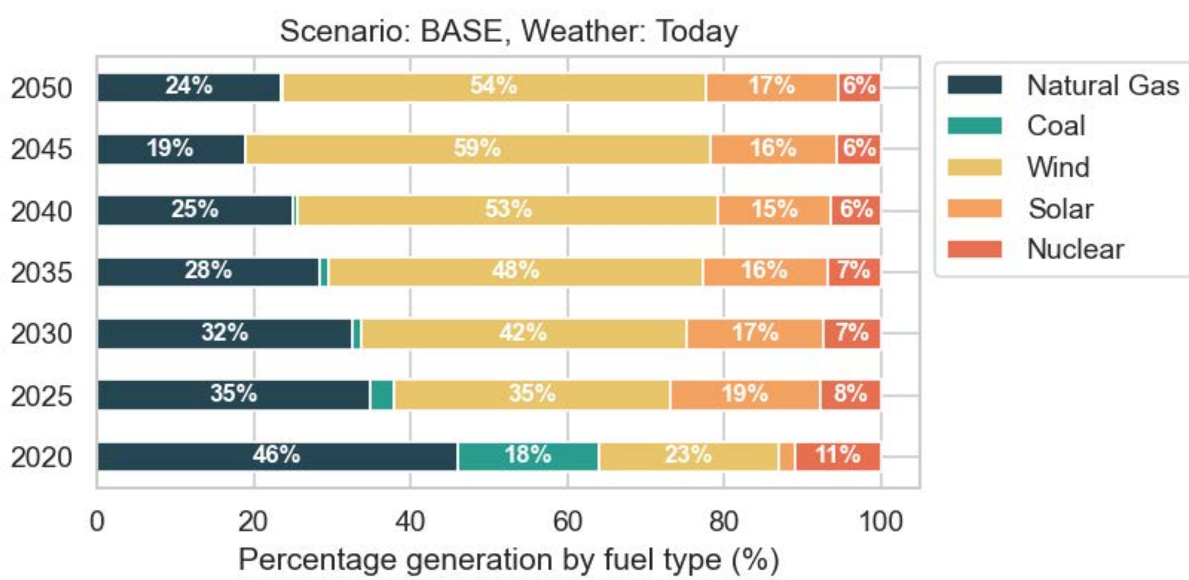


Figure 34: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the BASE scenario assuming Today's weather.

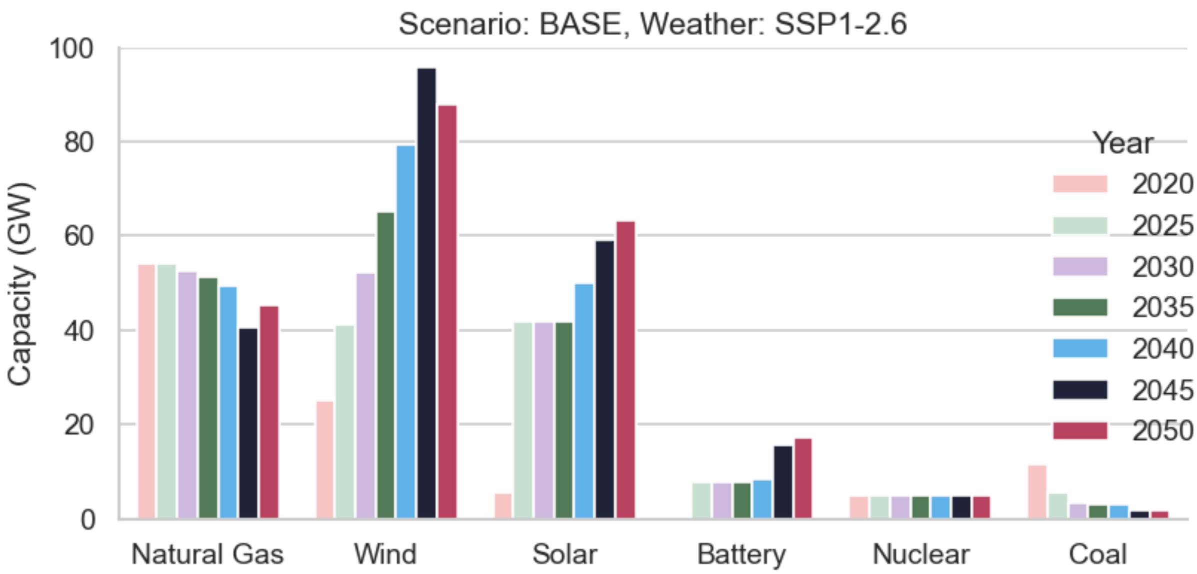


Figure 35: Figure showing the total capacity for various generation types in the ERCOT grid in the BASE scenario assuming SSP1-2.6 weather.

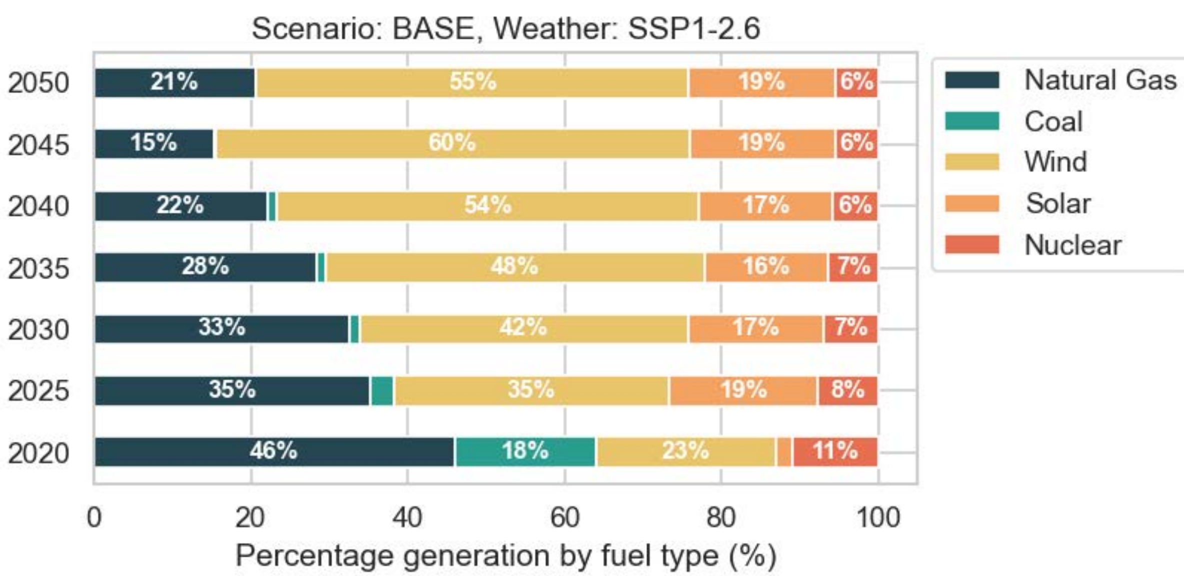


Figure 36: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the BASE scenario assuming SSP1-2.6 weather.

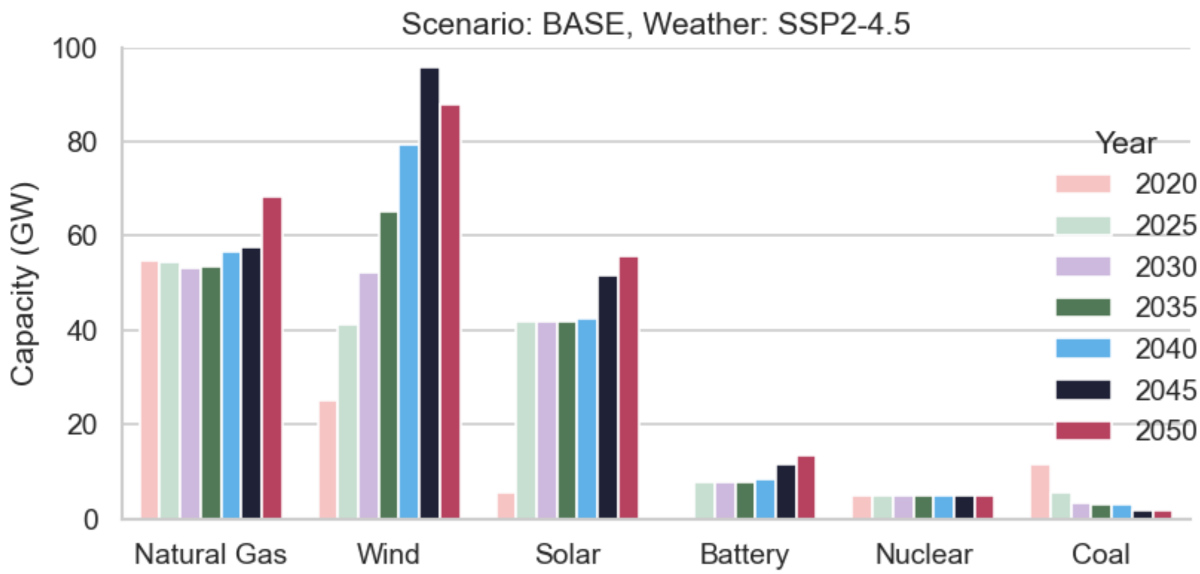
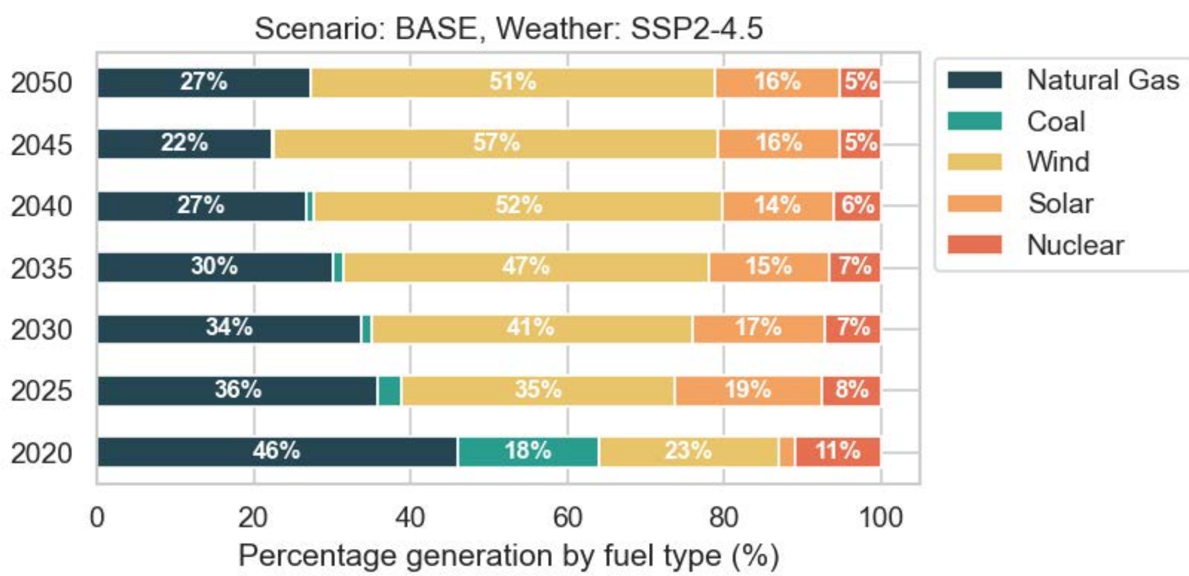


Figure 37: Figure showing the total capacity for various generation types in the ERCOT grid in the BASE scenario assuming SSP2-4.5 weather.



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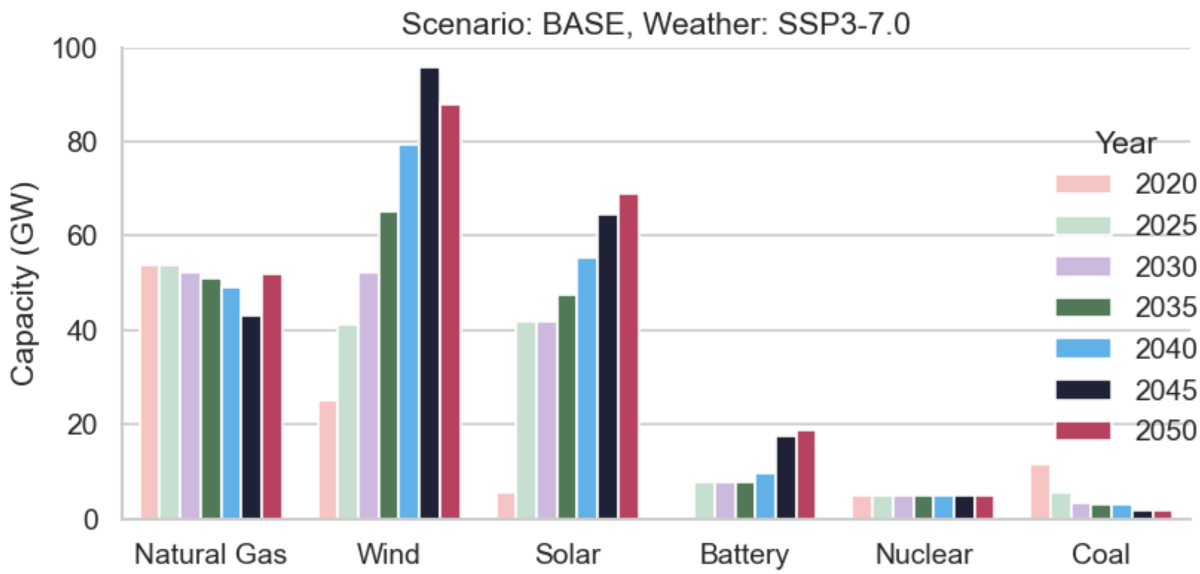
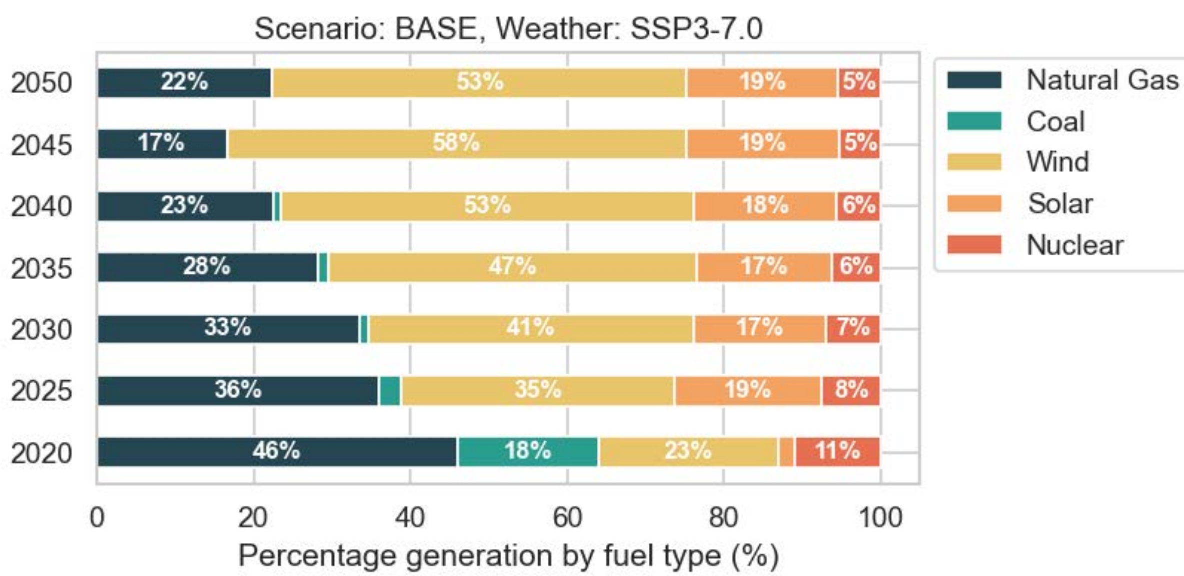


Figure 39: Figure showing the total capacity for various generation types in the ERCOT grid in the BASE scenario assuming SPP3-7.0 weather.



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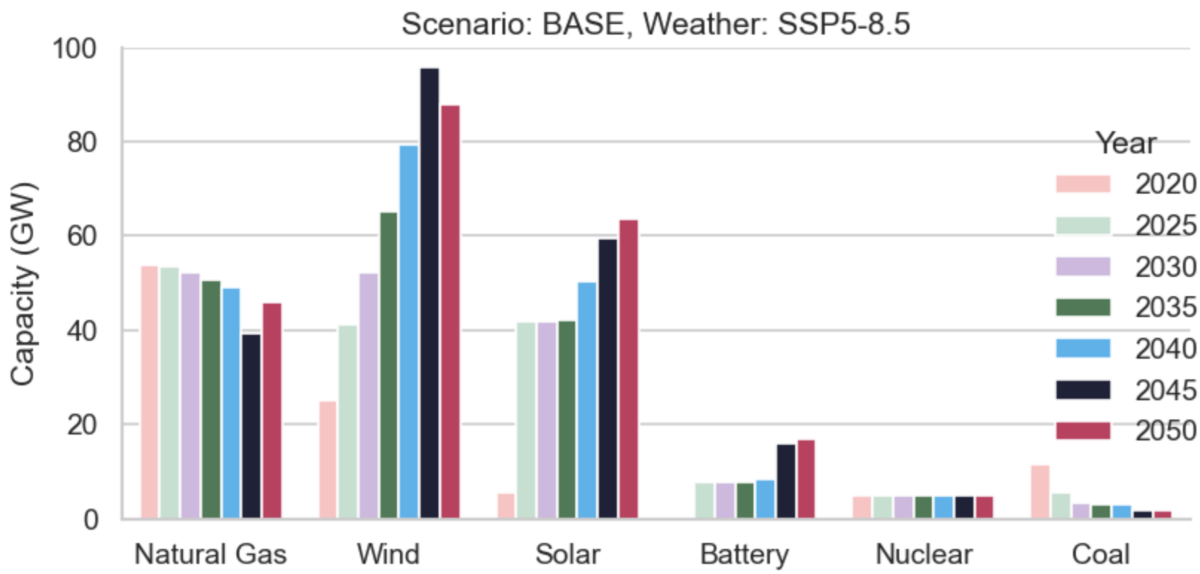


Figure 41: Figure showing the total capacity for various generation types in the ERCOT grid in the BASE scenario assuming SSP5-8.5 weather.

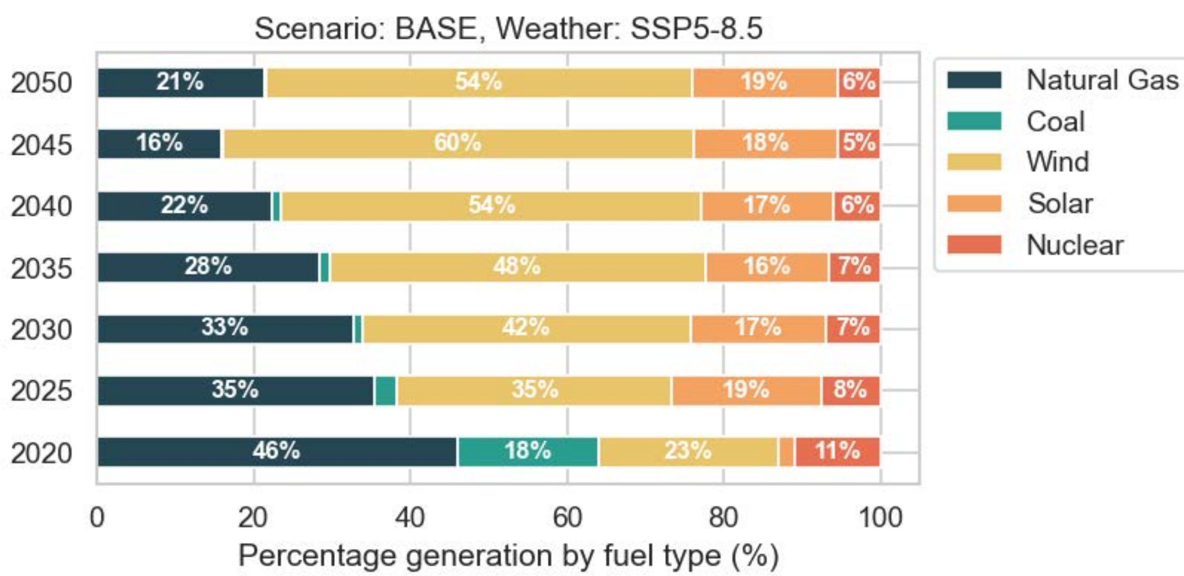
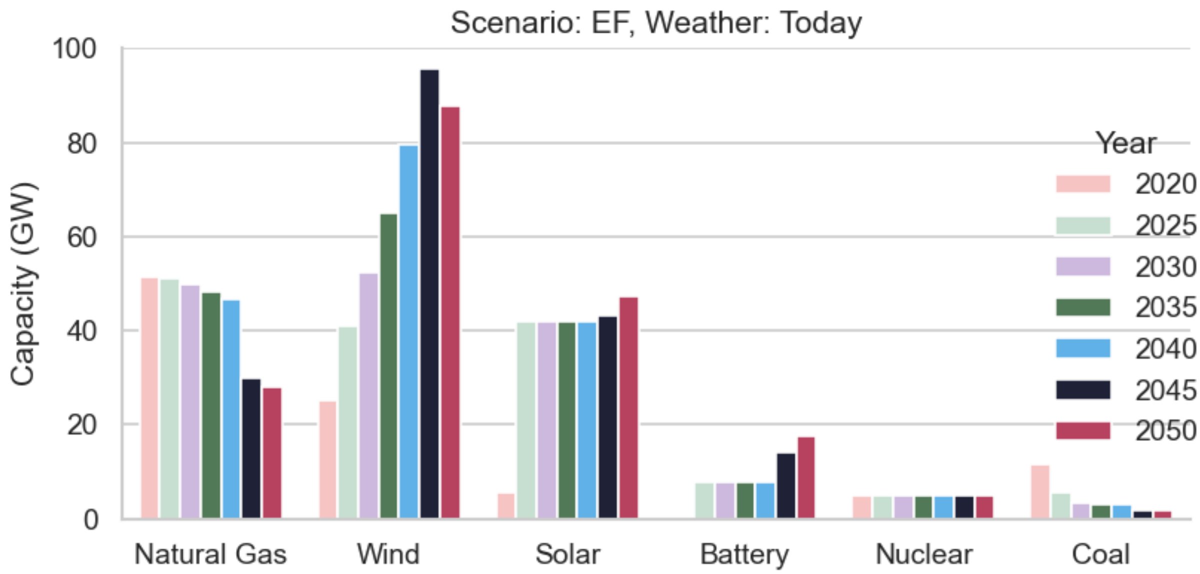


Figure 42: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the BASE scenario assuming SSP5-8.5 weather.



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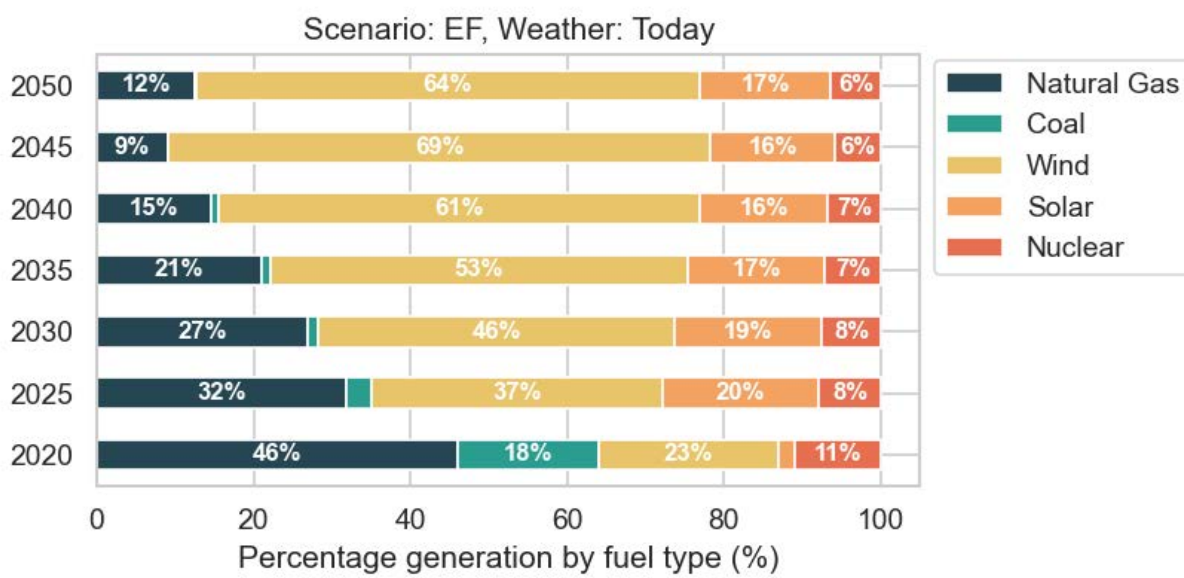


Figure 44: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF scenario assuming Today's weather.

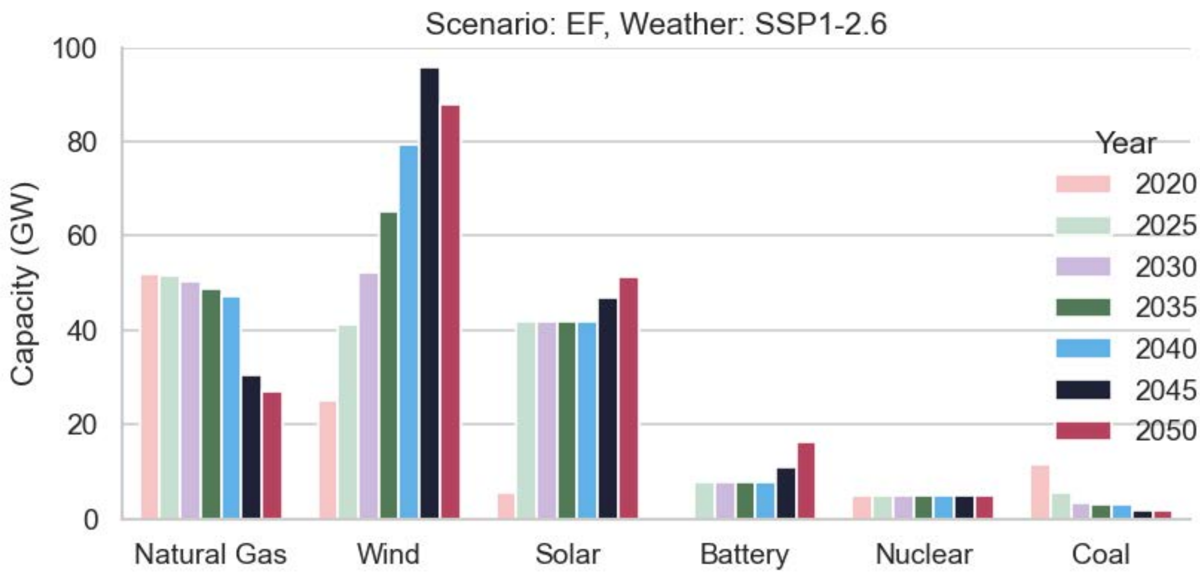
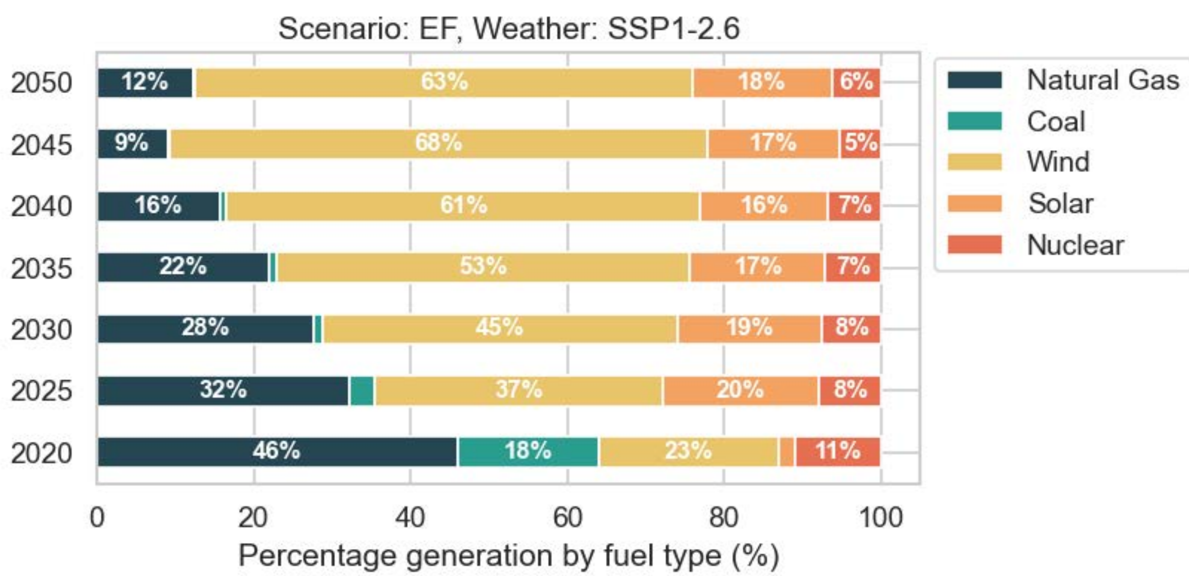


Figure 45: Figure showing the total capacity for various generation types in the ERCOT grid in the EF scenario assuming SSP1-2.6 weather.



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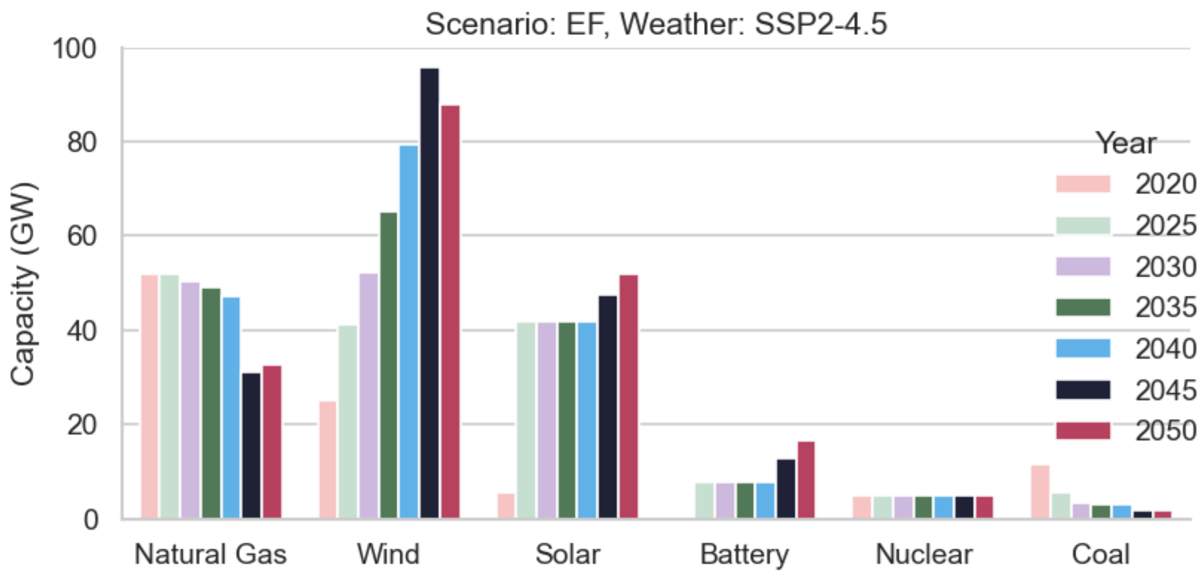
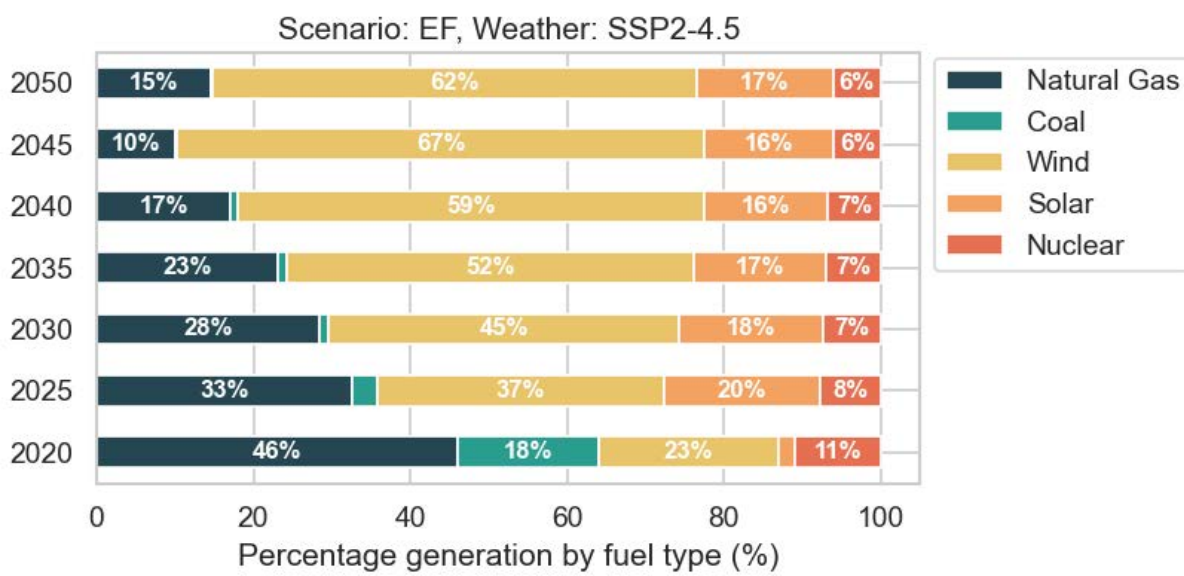


Figure 47: Figure showing the total capacity for various generation types in the ERCOT grid in the EF scenario assuming SSP2-4.5 weather.



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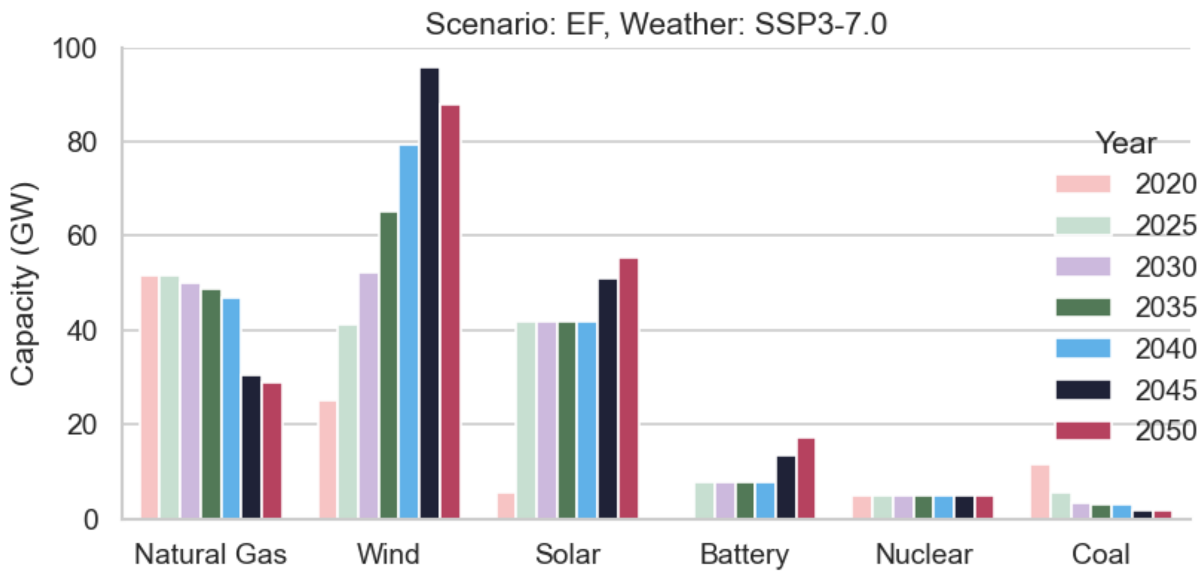

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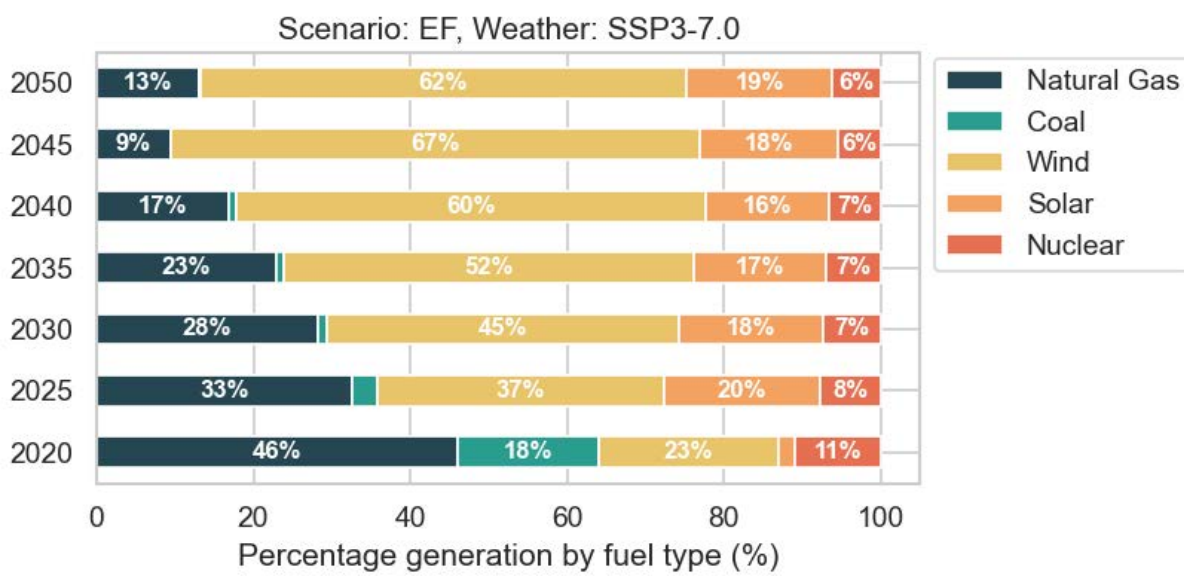

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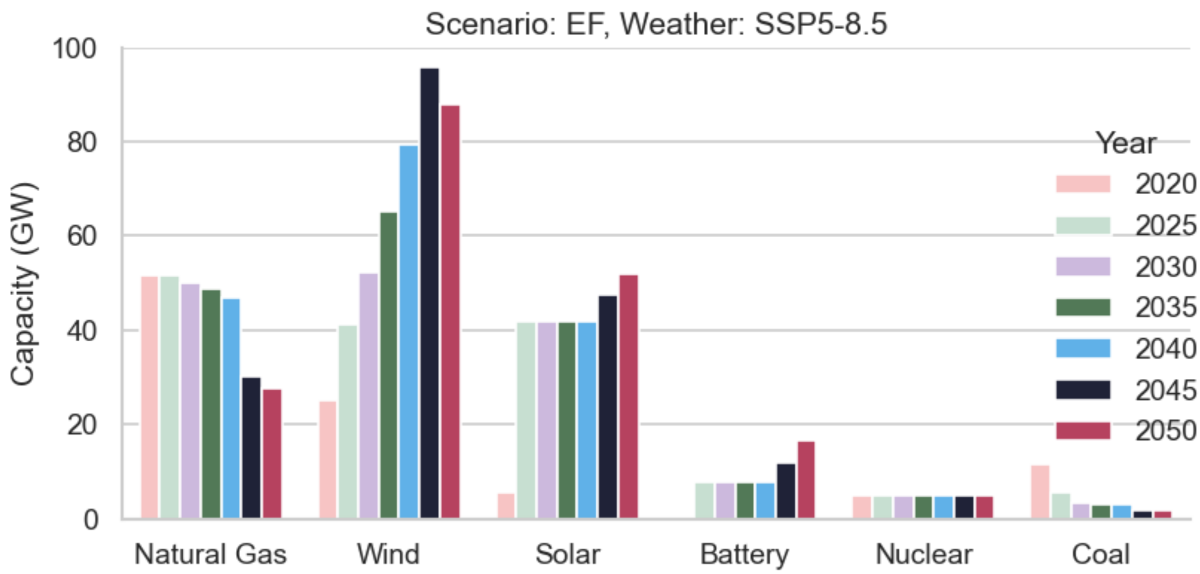
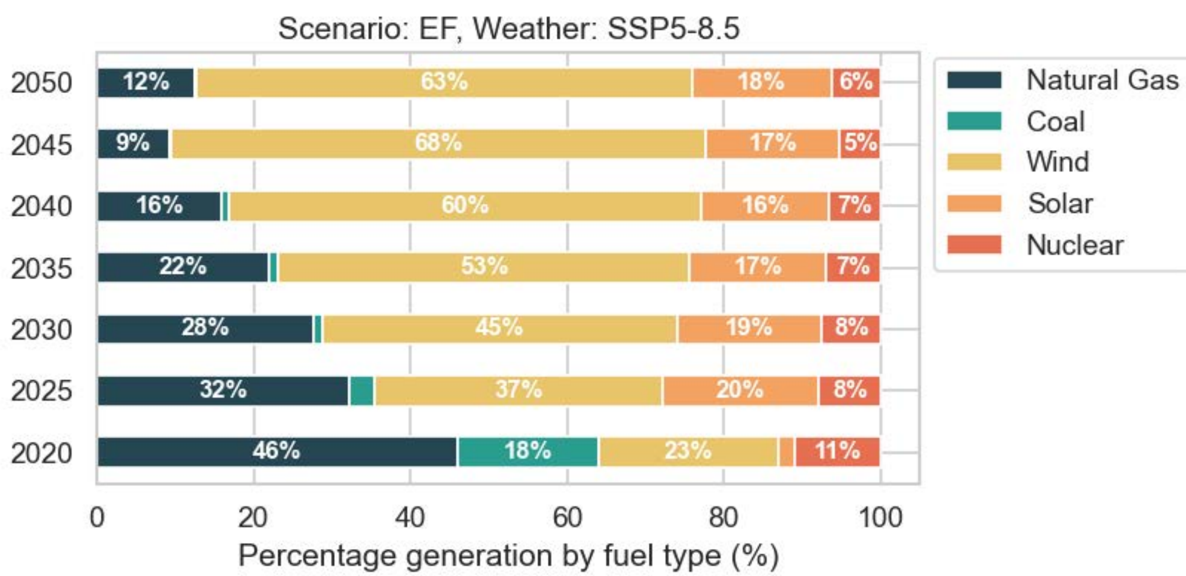


Figure 51: Figure showing the total capacity for various generation types in the ERCOT grid in the EF scenario assuming SSP5-8.5 weather.



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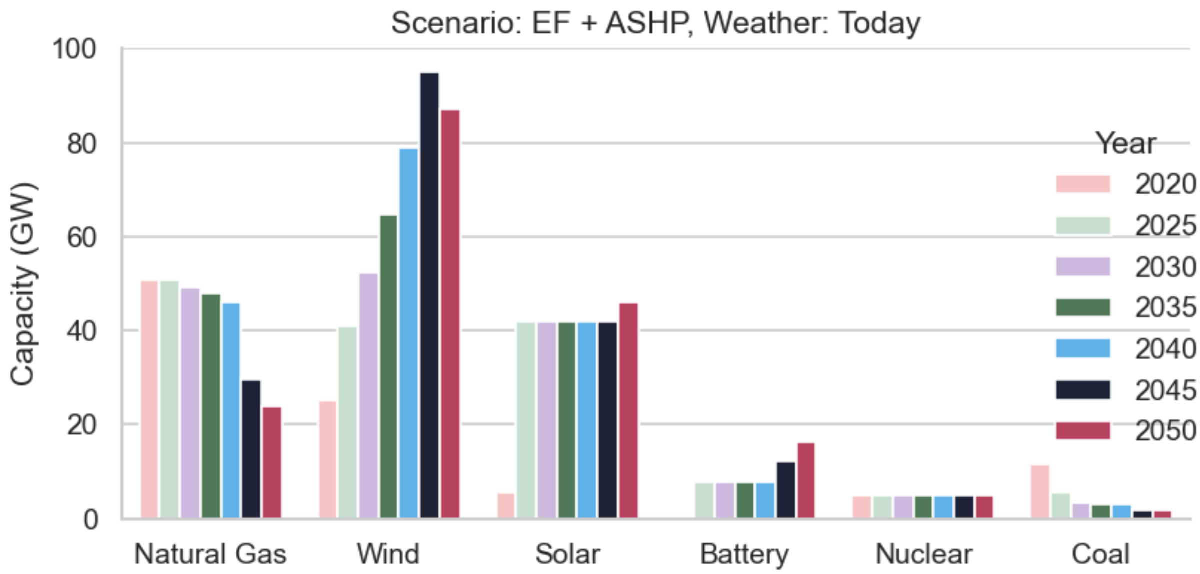
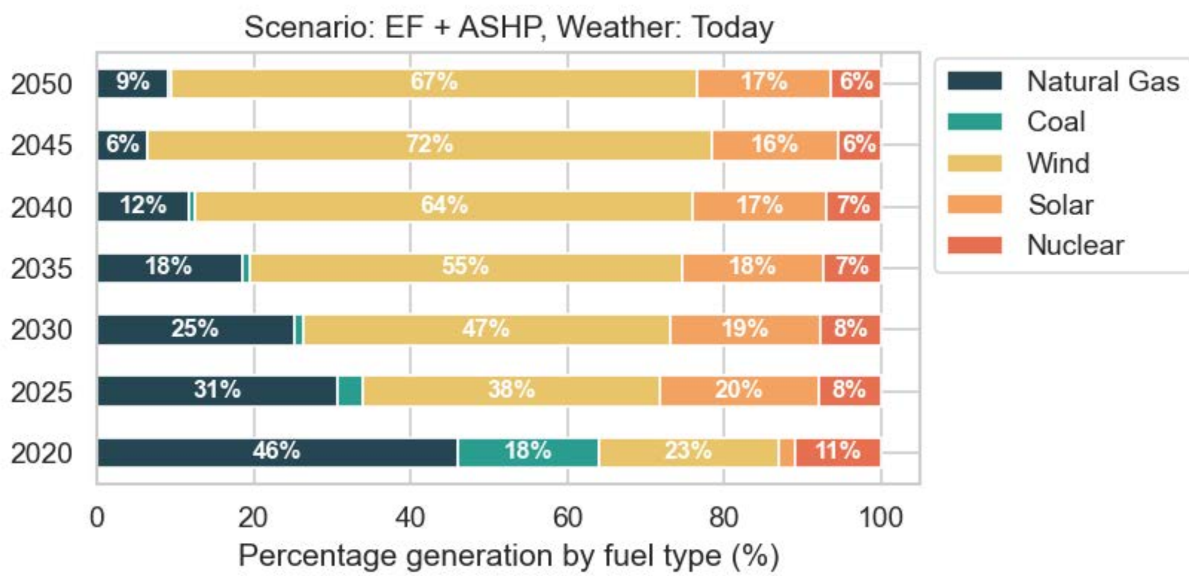


Figure 53: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP scenario assuming Today's weather.



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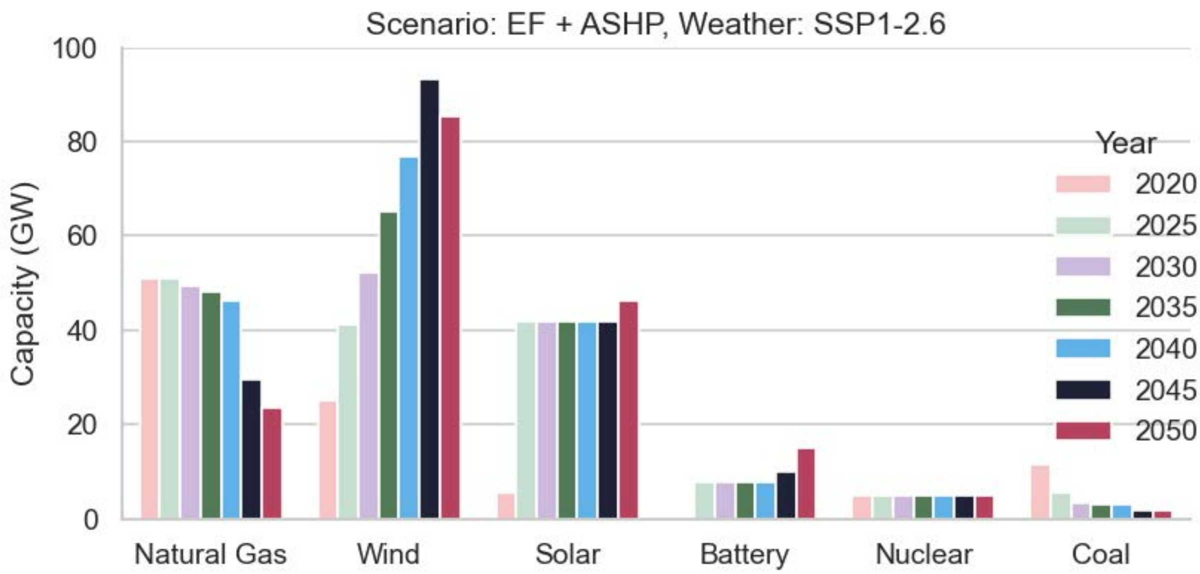

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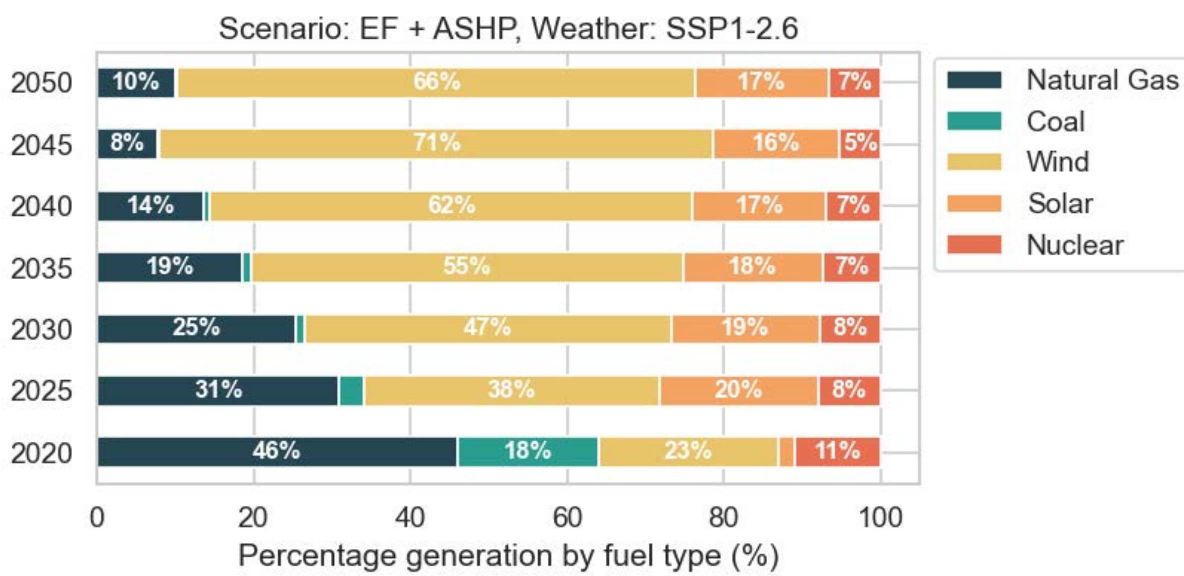

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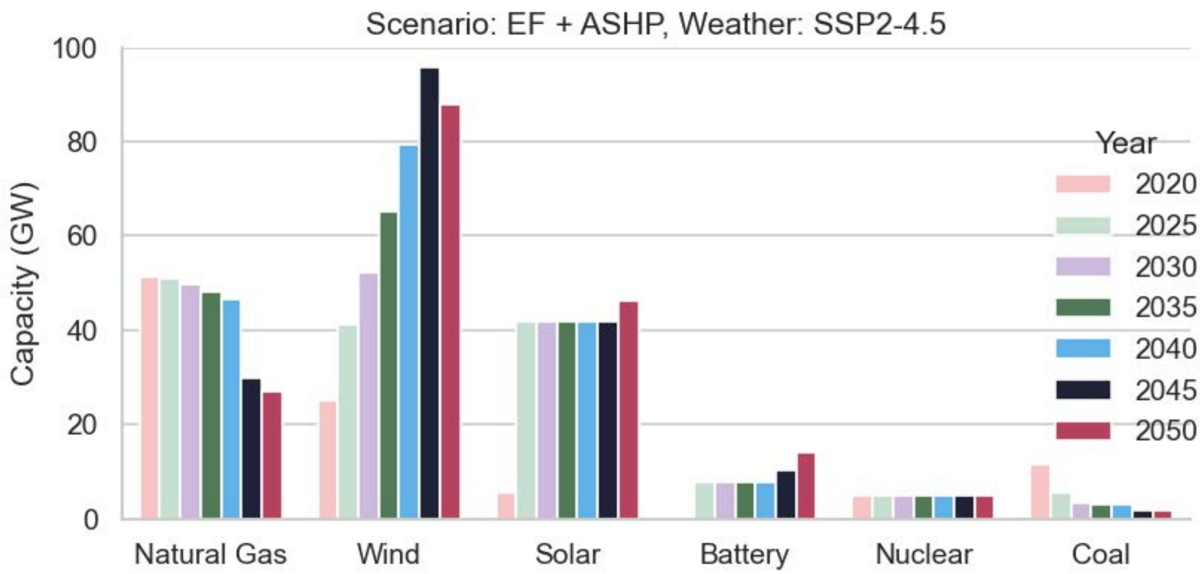

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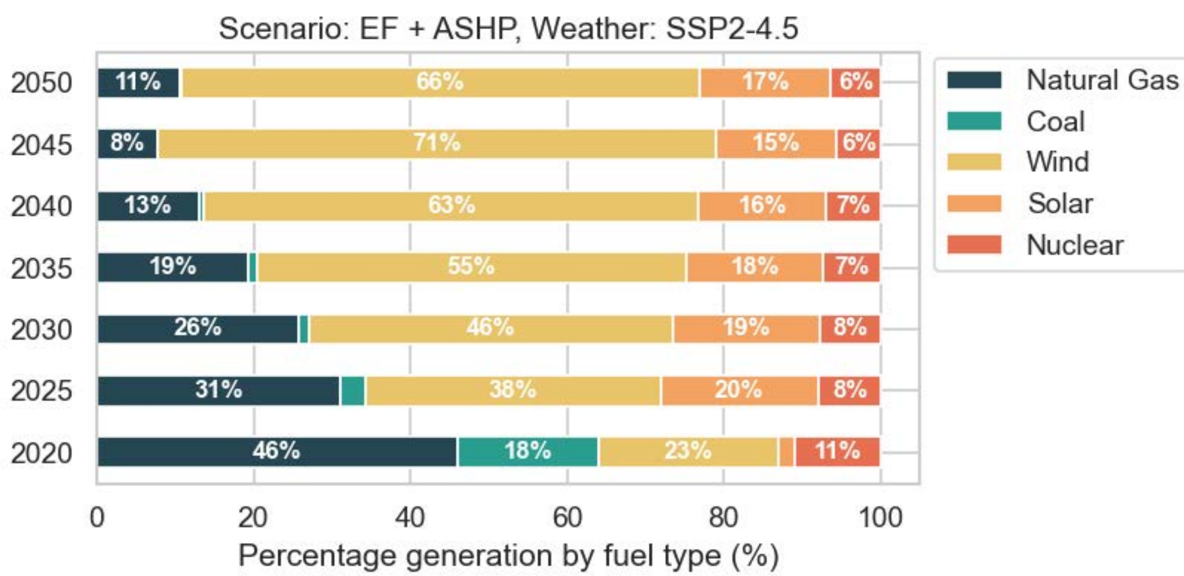

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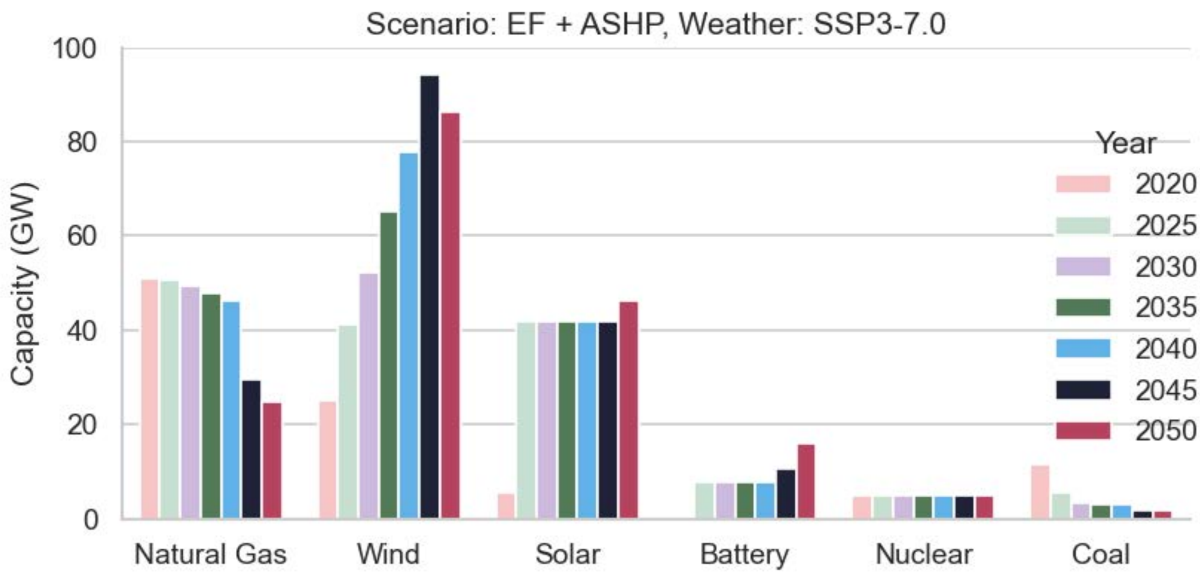

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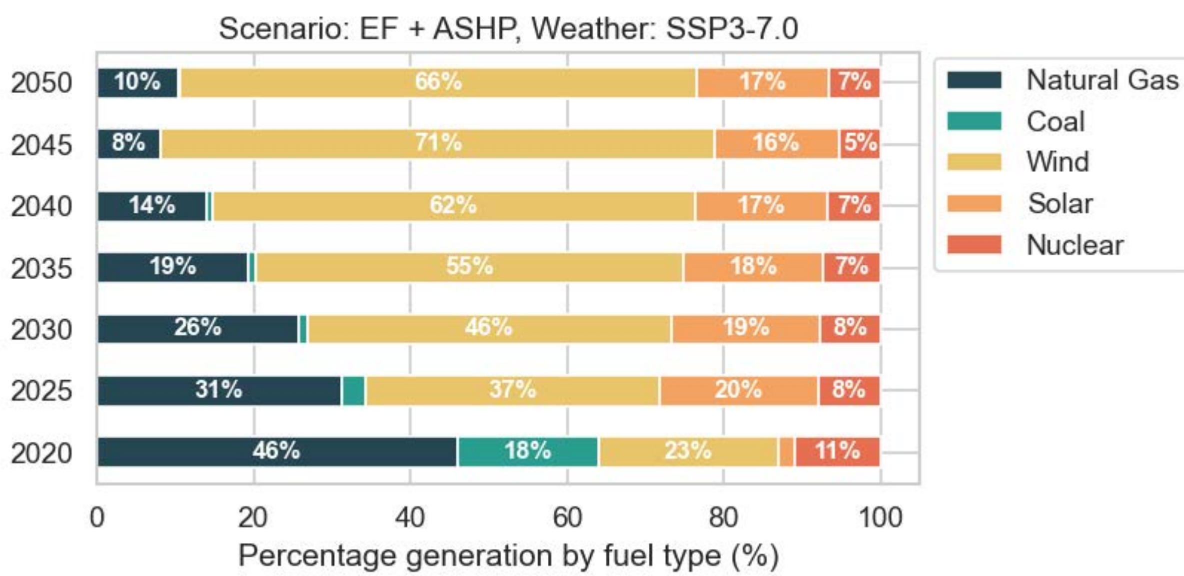

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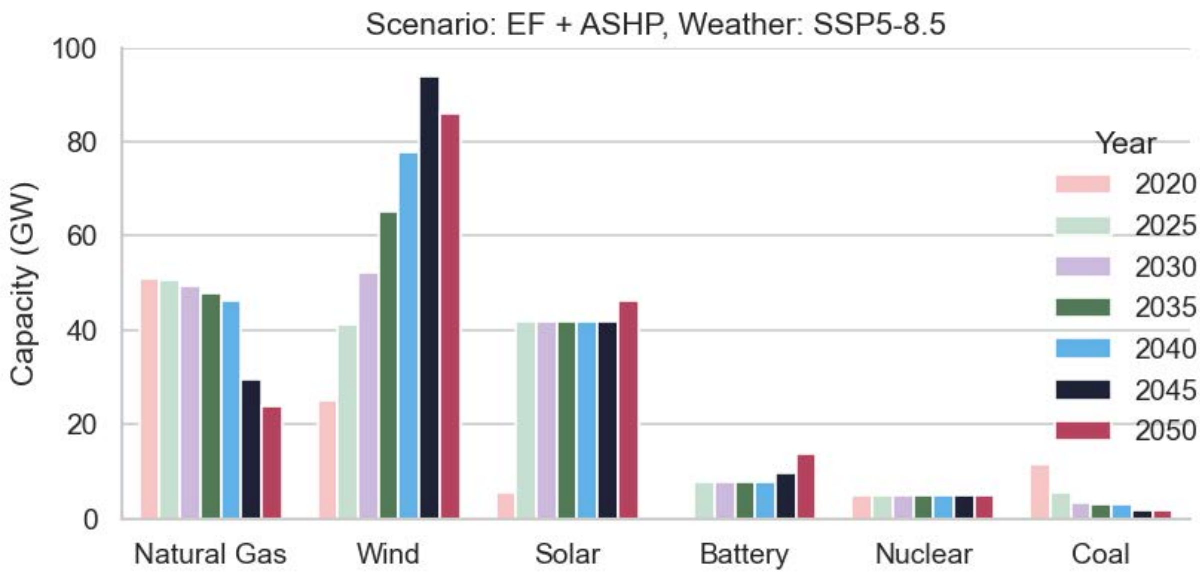


Figure 61: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP scenario assuming SSP5-8.5 weather.

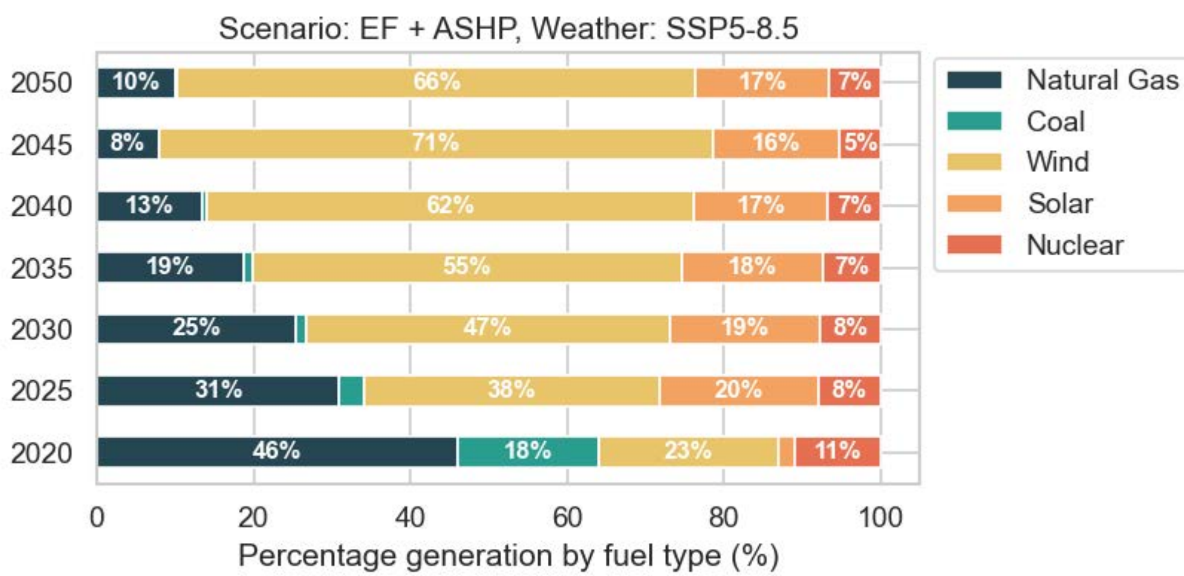


Figure 62: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP scenario assuming SSP5-8.5 weather.

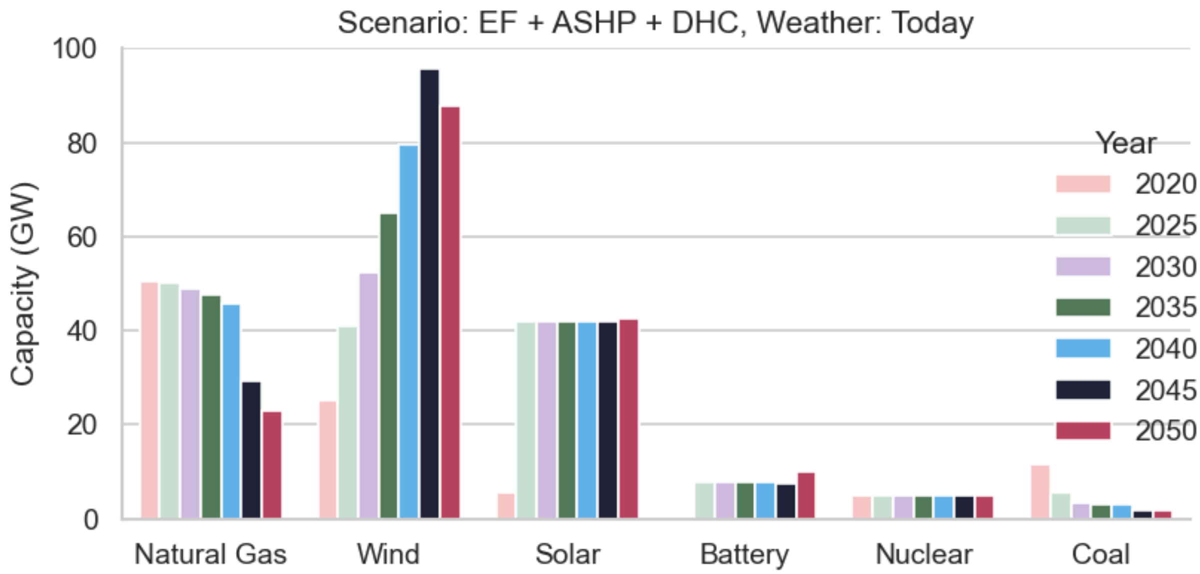


Figure 63: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + DHC scenario assuming Today's weather.

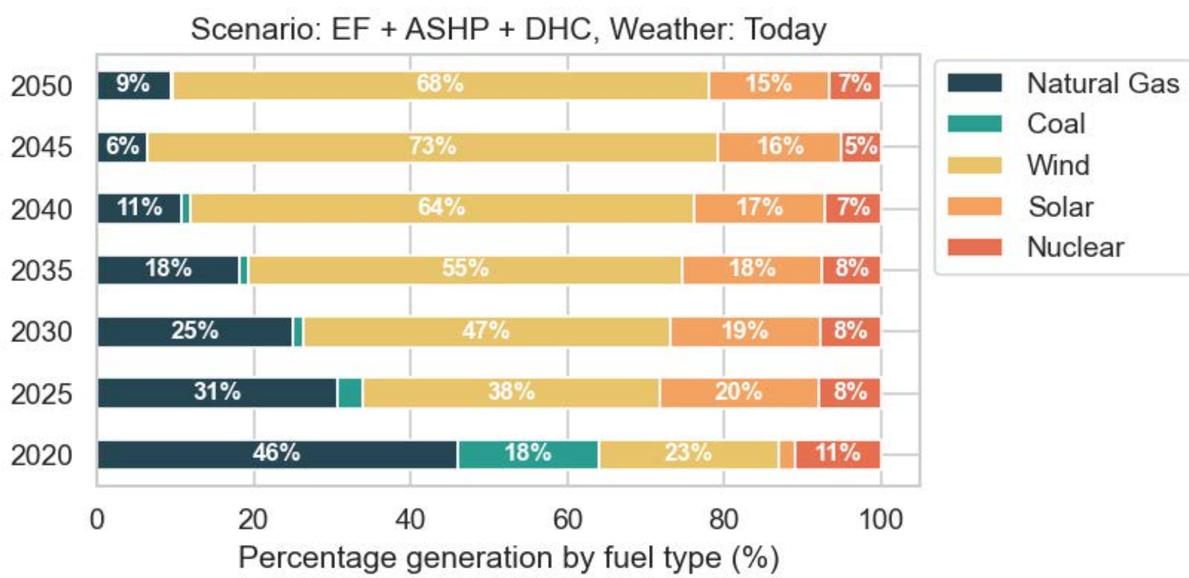


Figure 64: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + DHC scenario assuming Today's weather.

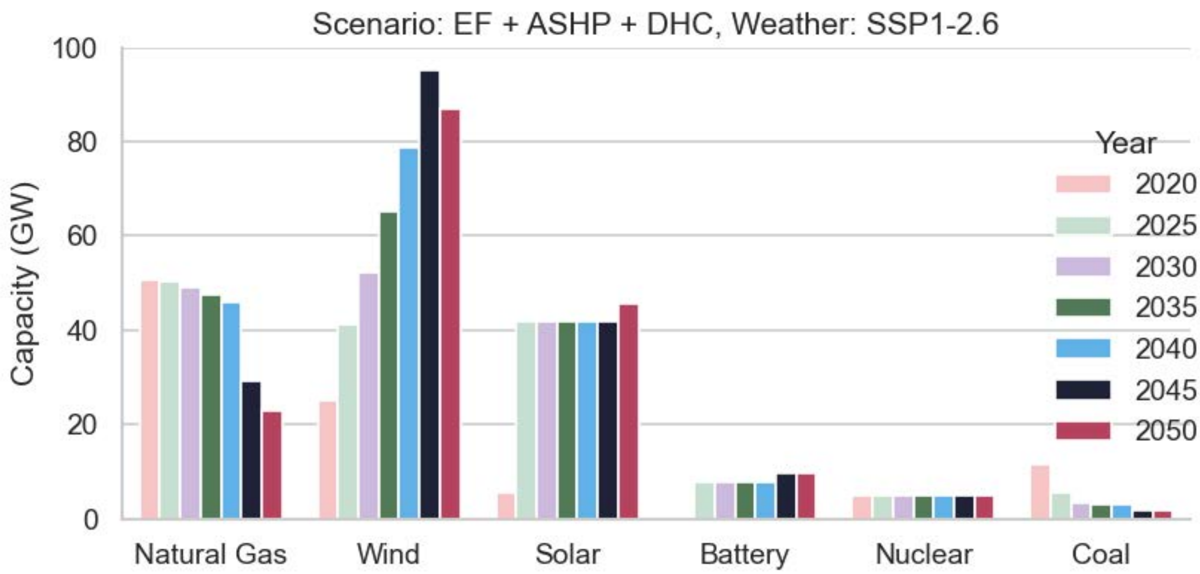


Figure 65: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + DHC scenario assuming SSP1-2.6 weather.

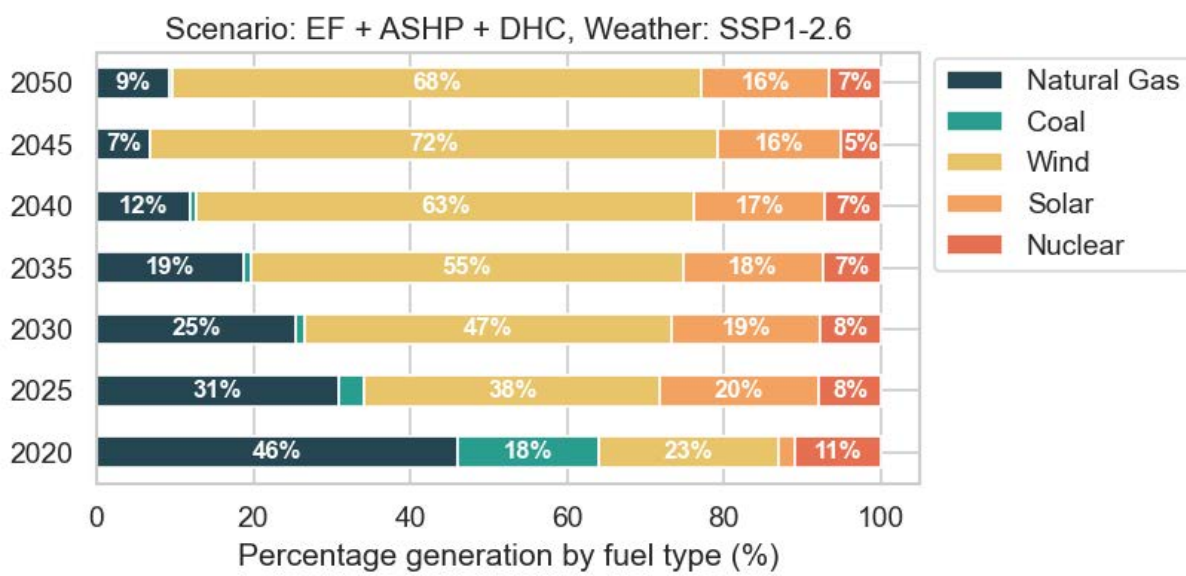


Figure 66: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + DHC scenario assuming SSP1-2.6 weather.

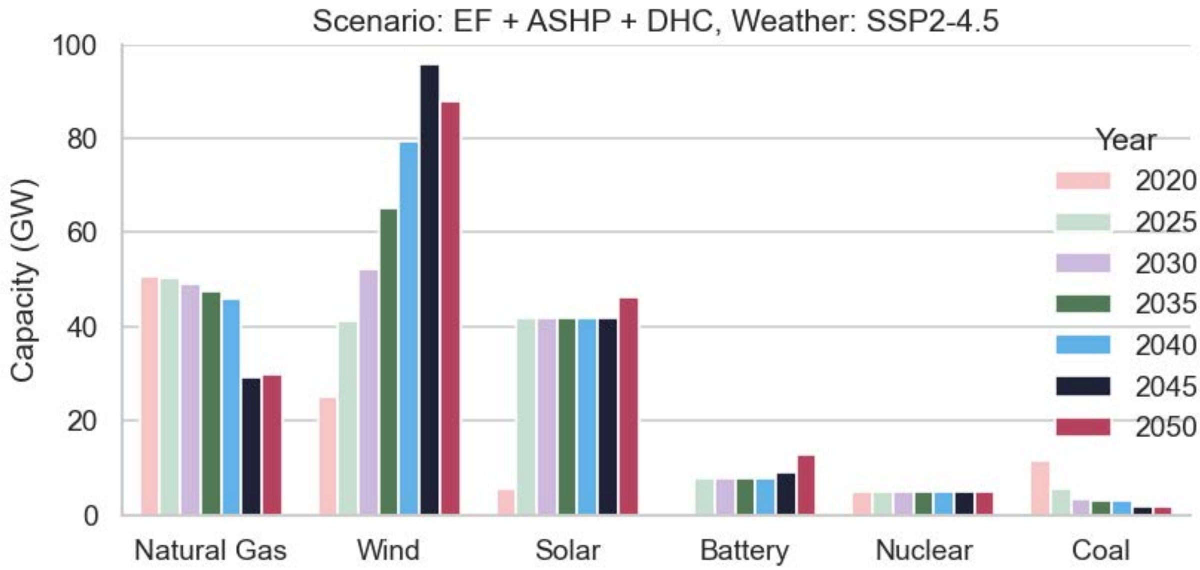


Figure 67: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + DHC scenario assuming SSP2-4.5 weather.

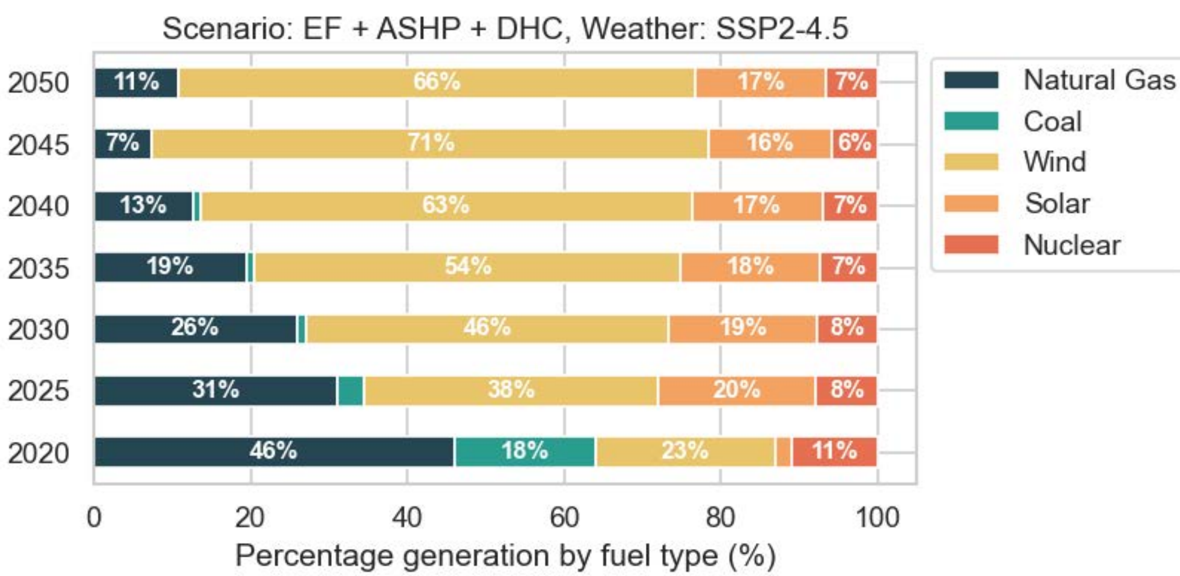


Figure 68: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + DHC scenario assuming SSP2-4.5 weather.

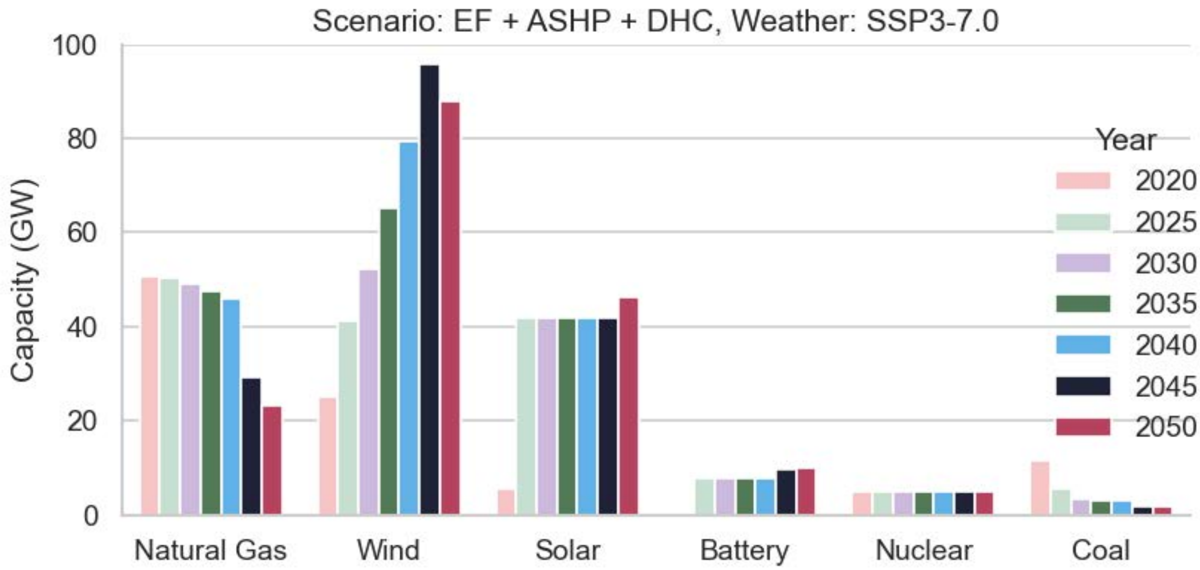


Figure 69: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + DHC scenario assuming SPP3-7.0 weather.

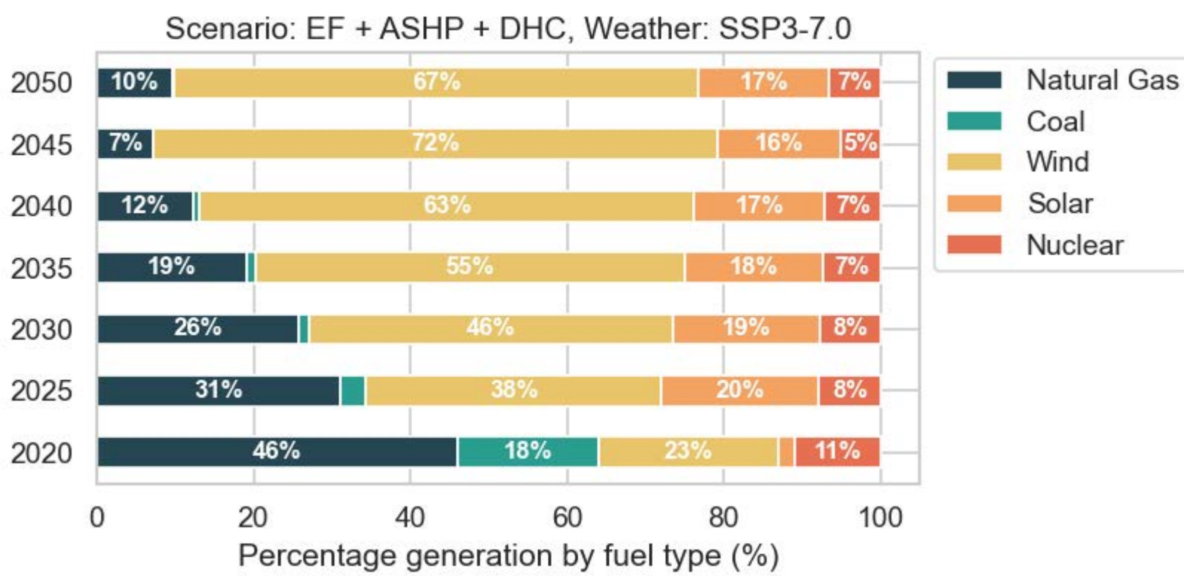


Figure 70: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + DHC scenario assuming SPP3-7.0 weather.

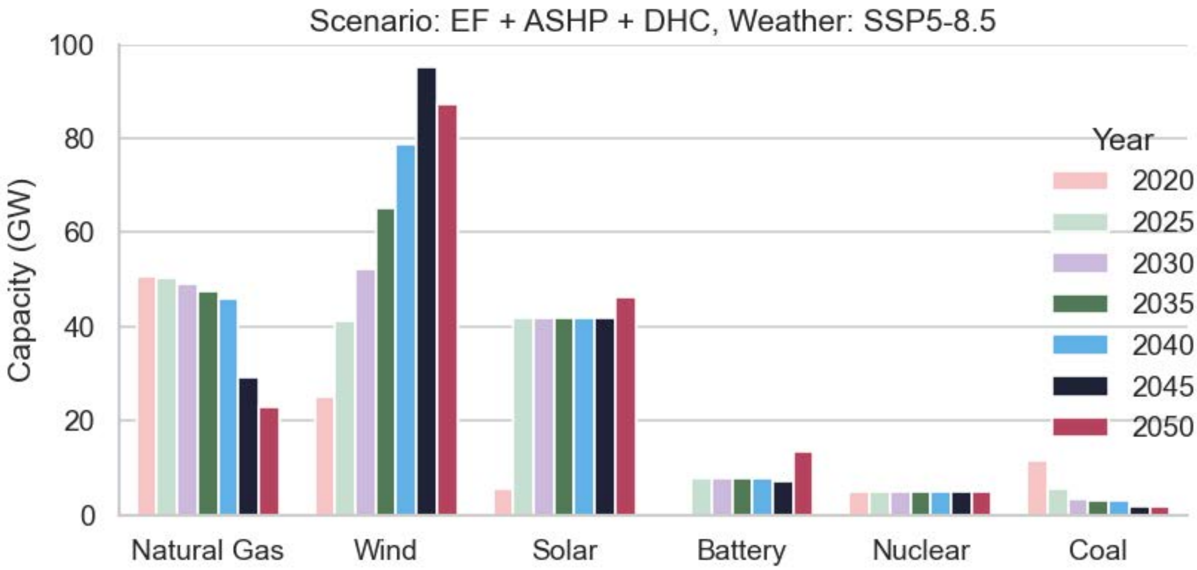


Figure 71: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + DHC scenario assuming SSP5-8.5 weather.

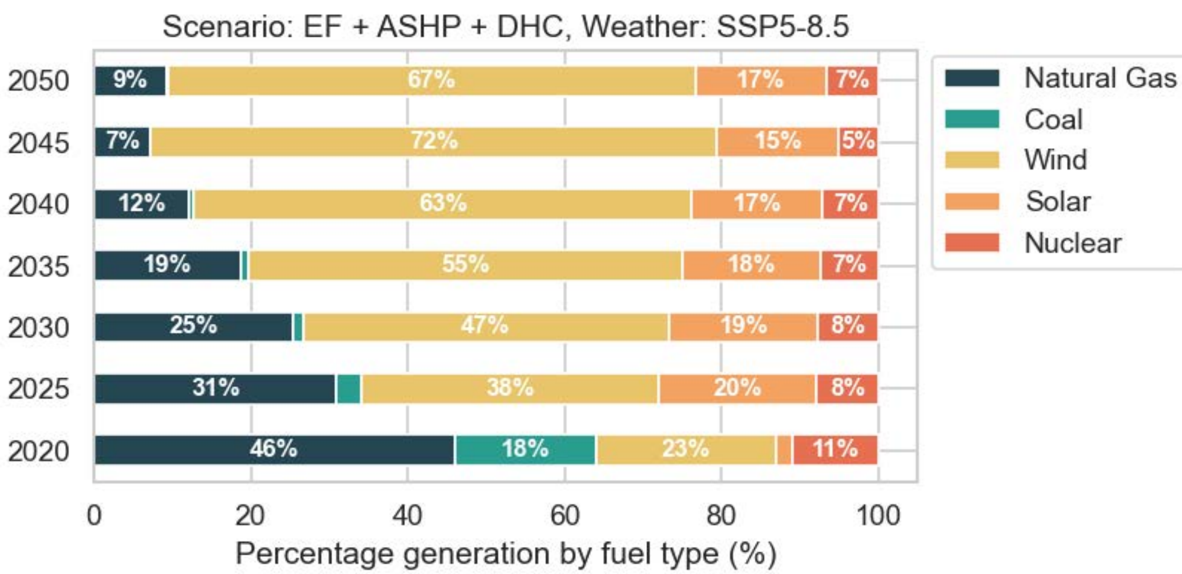


Figure 72: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + DHC scenario assuming SSP5-8.5 weather.

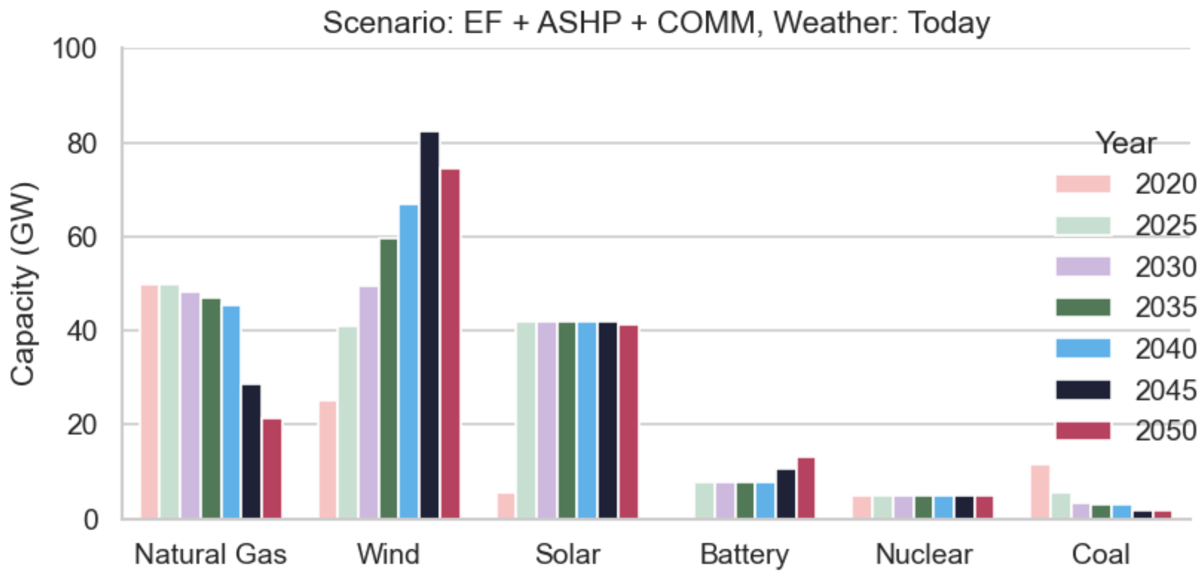


Figure 73: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM scenario assuming Today's weather.

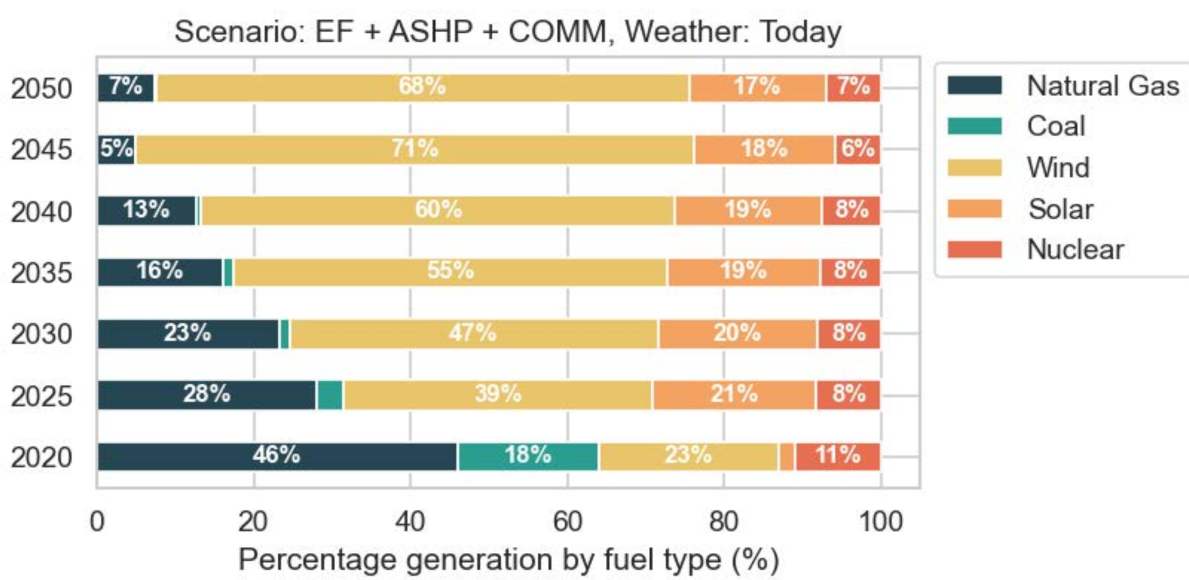


Figure 74: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM scenario assuming Today's weather.

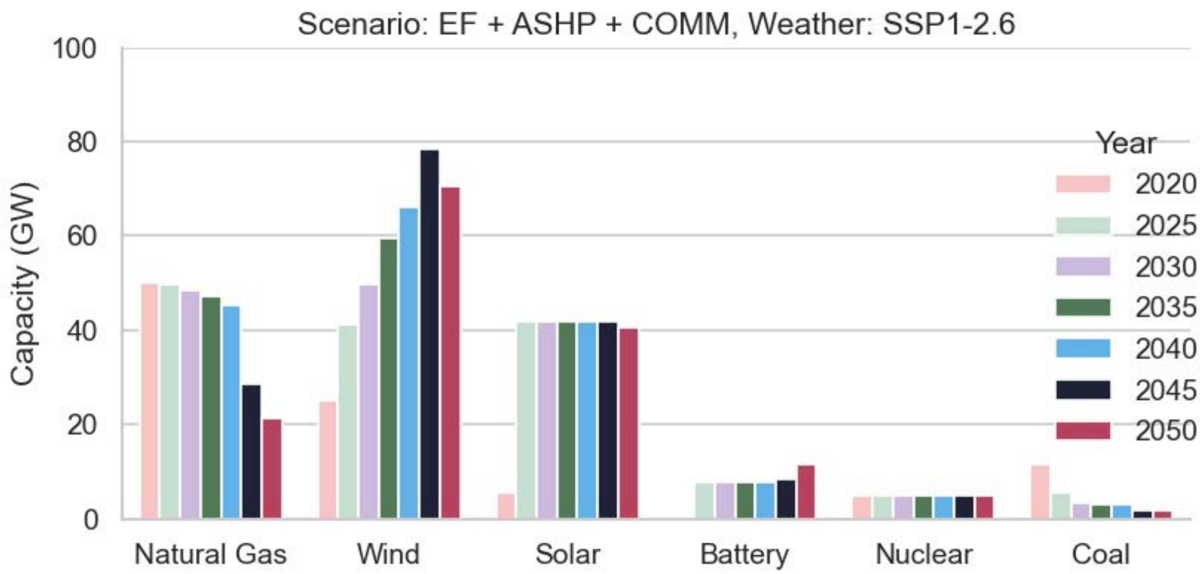


Figure 75: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM scenario assuming SSP1-2.6 weather.

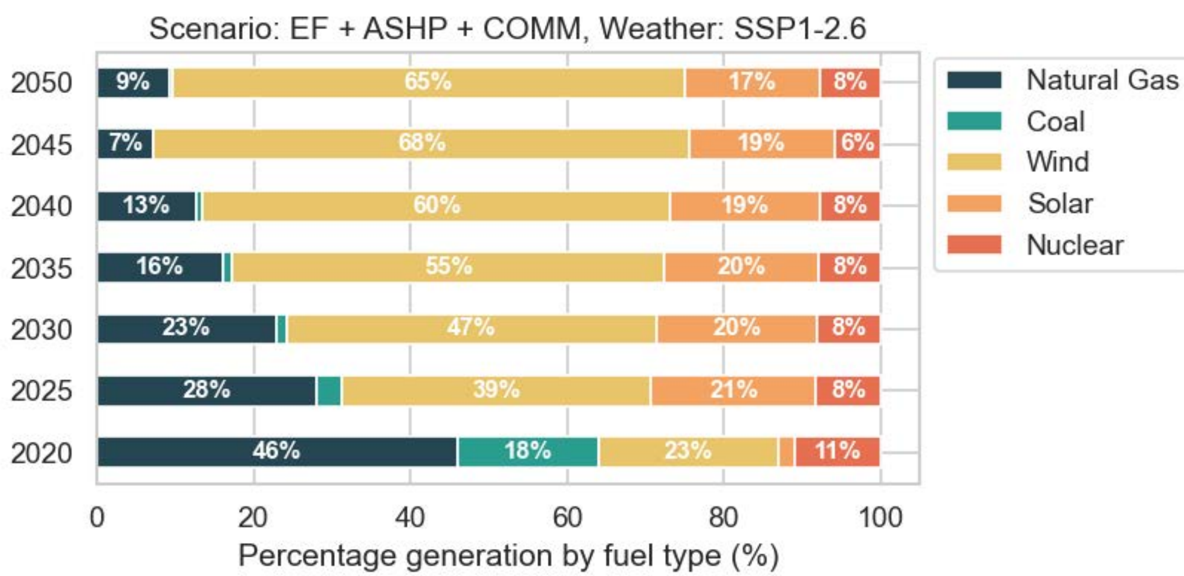


Figure 76: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM scenario assuming SSP1-2.6 weather.

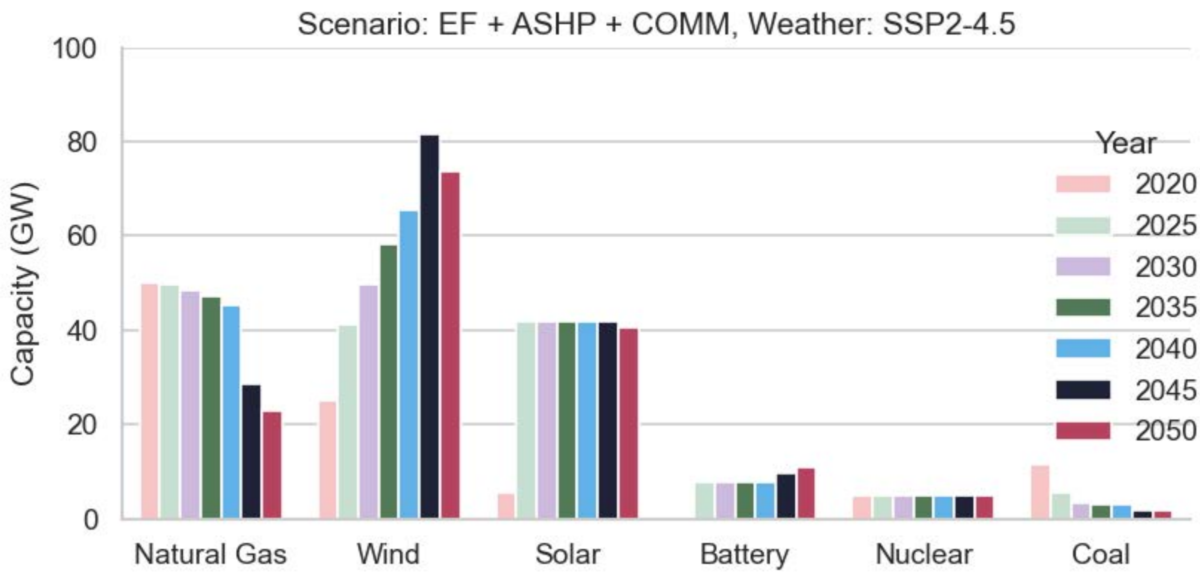


Figure 77: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM scenario assuming SSP2-4.5 weather.

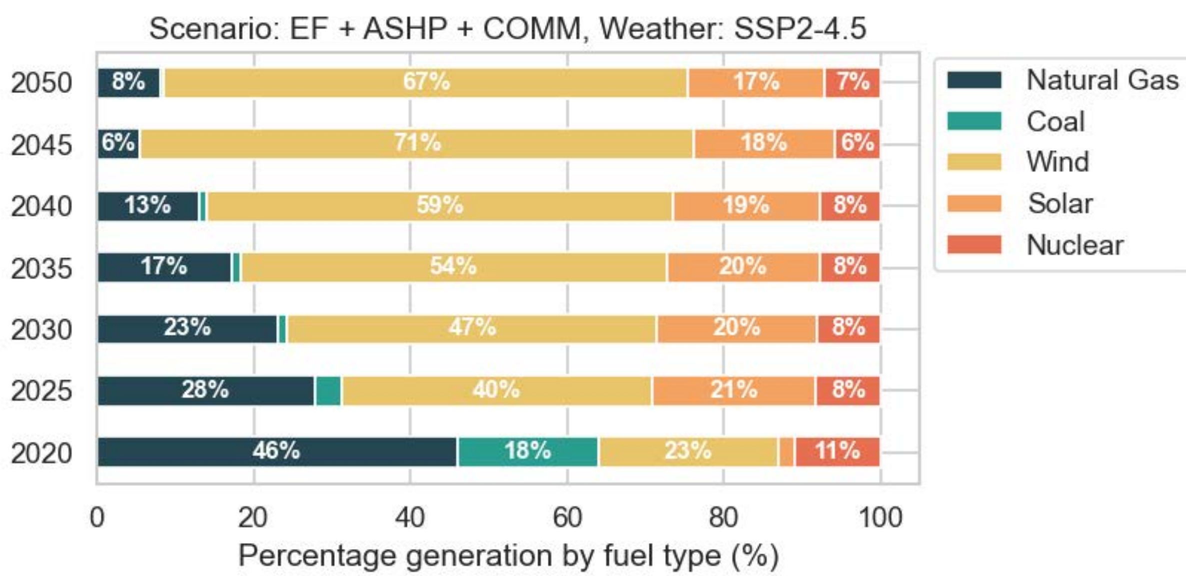


Figure 78: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM scenario assuming SSP2-4.5 weather.

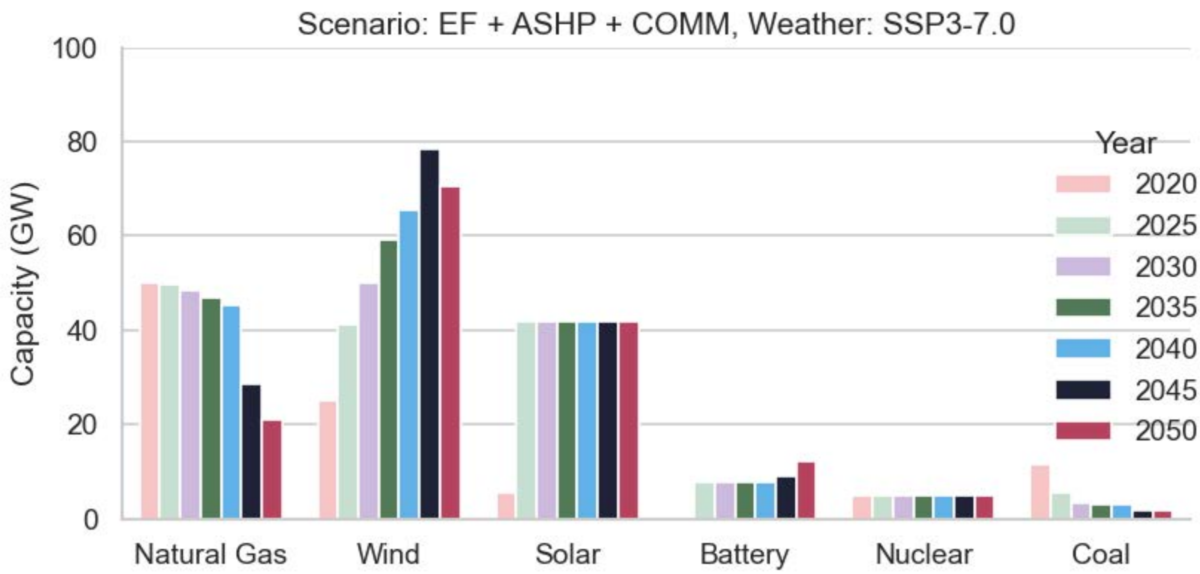


Figure 79: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM scenario assuming SPP3-7.0 weather.

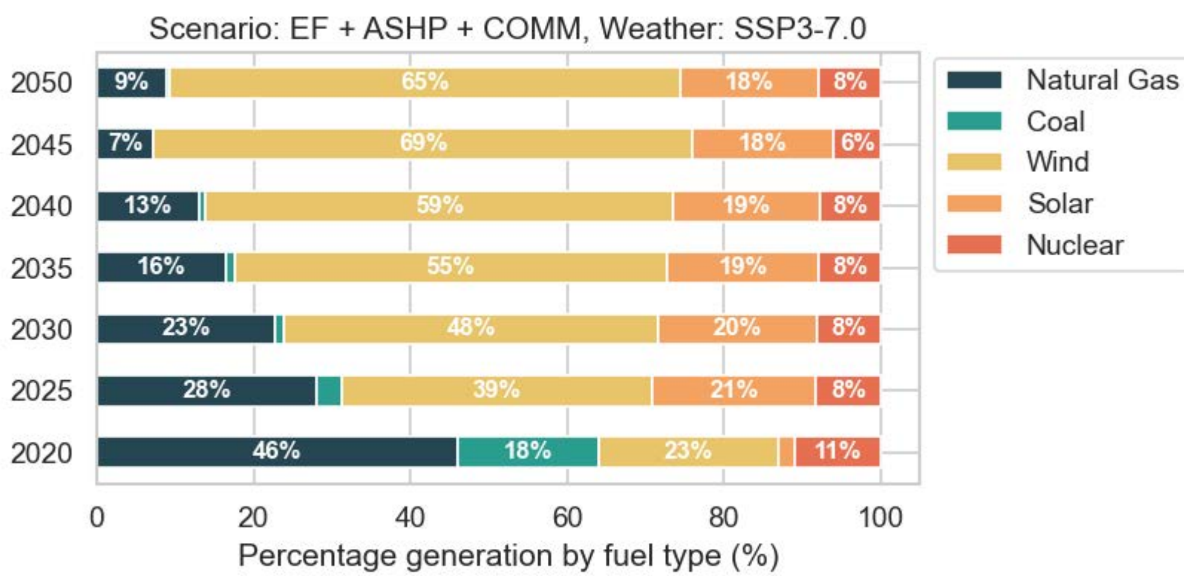


Figure 80: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM scenario assuming SPP3-7.0 weather.

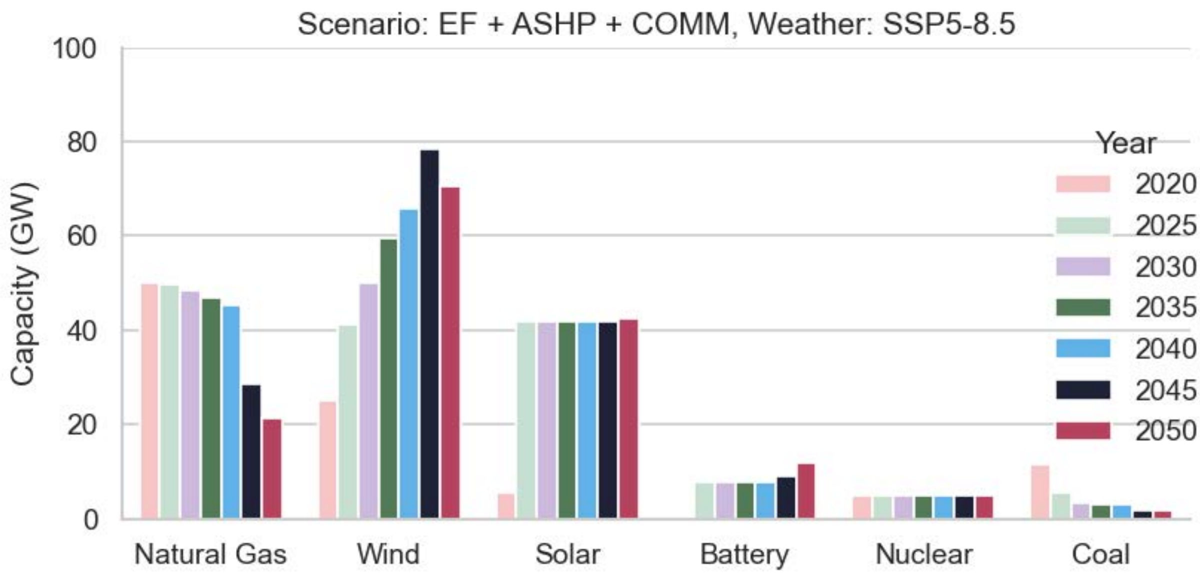


Figure 81: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM scenario assuming SSP5-8.5 weather.

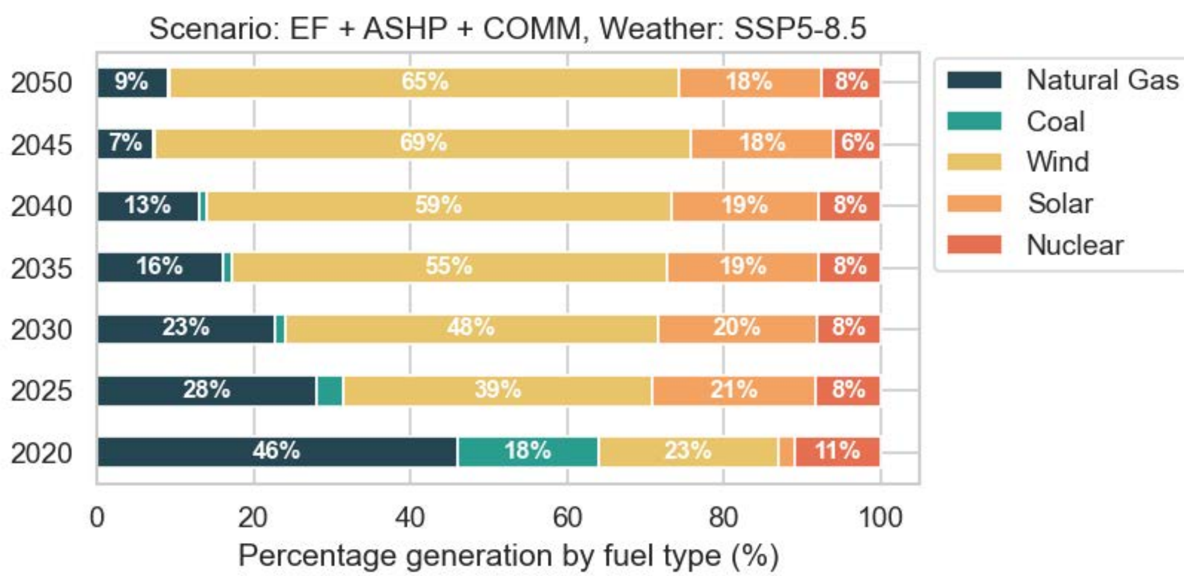


Figure 82: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM scenario assuming SSP5-8.5 weather.

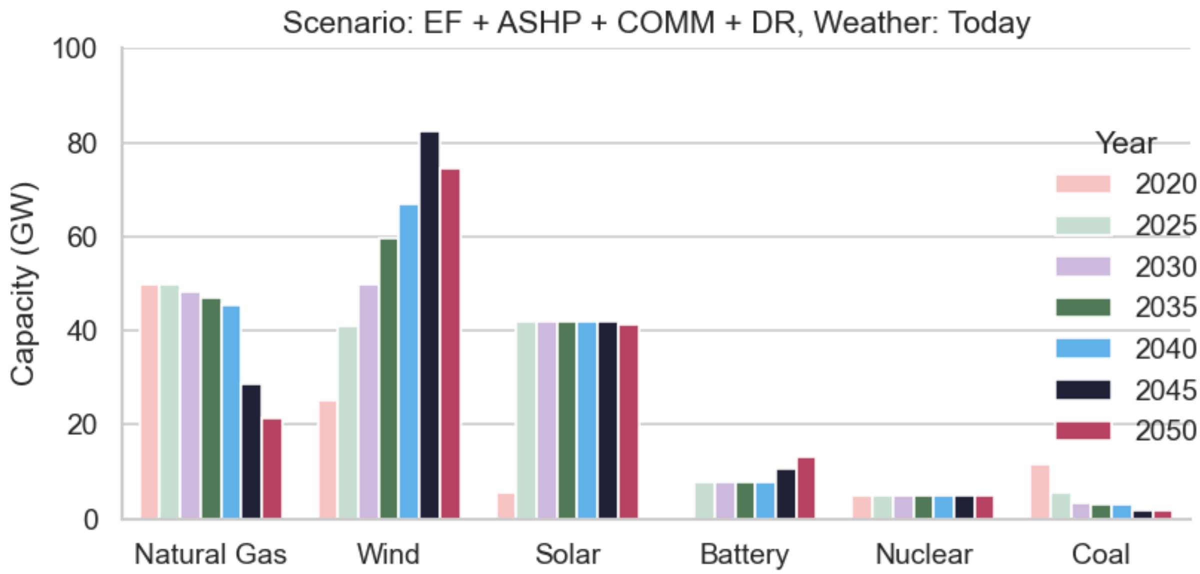


Figure 83: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM + DR scenario assuming Today's weather.

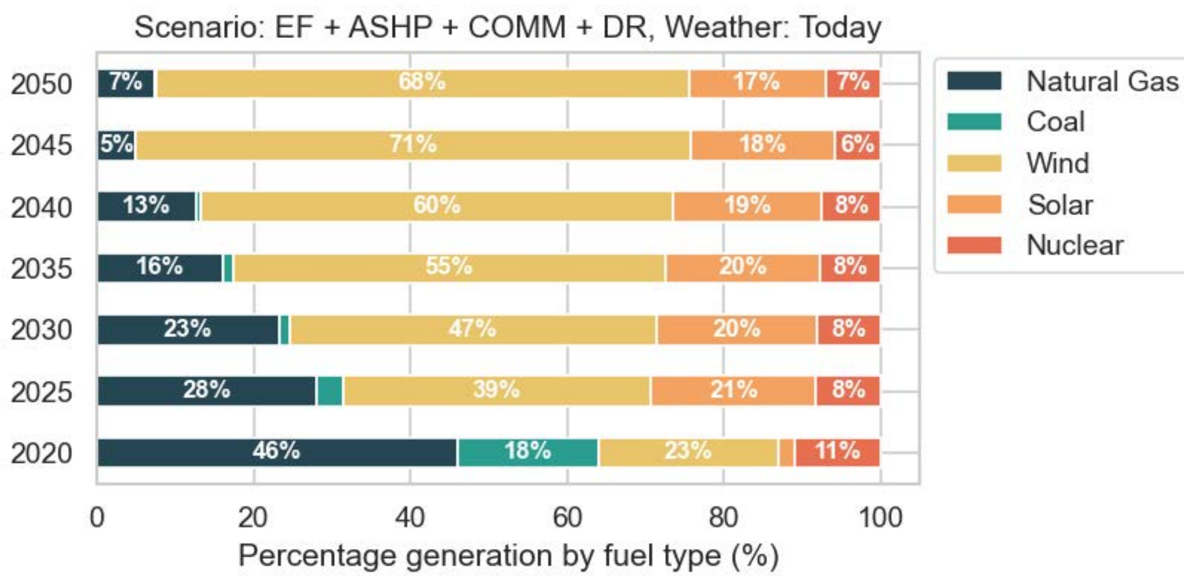


Figure 84: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM + DR scenario assuming Today's weather.

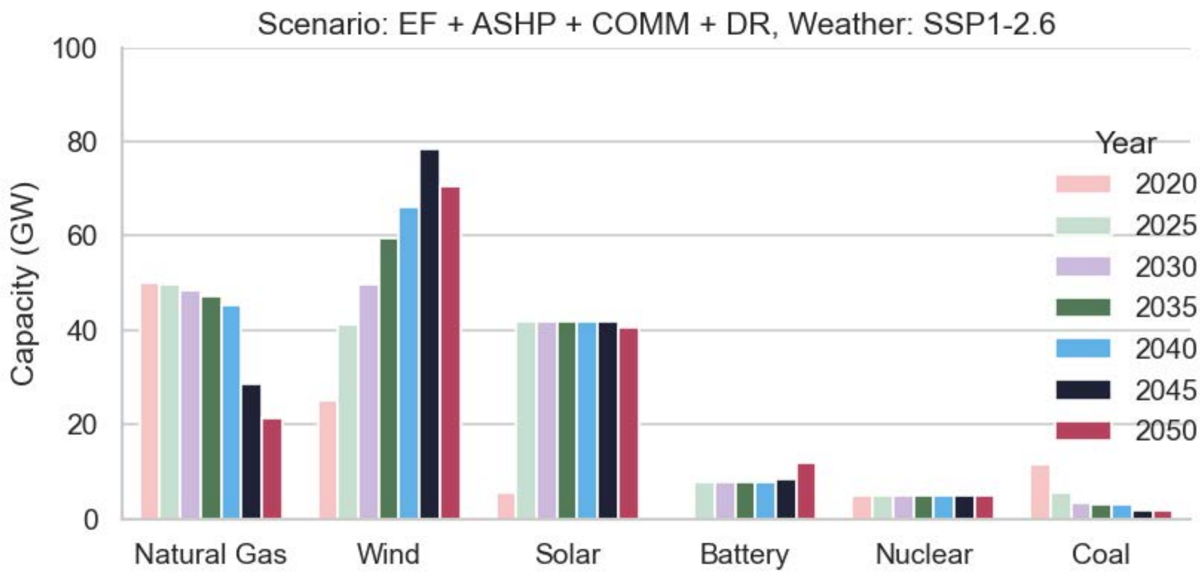


Figure 85: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM + DR scenario assuming SSP1-2.6 weather.

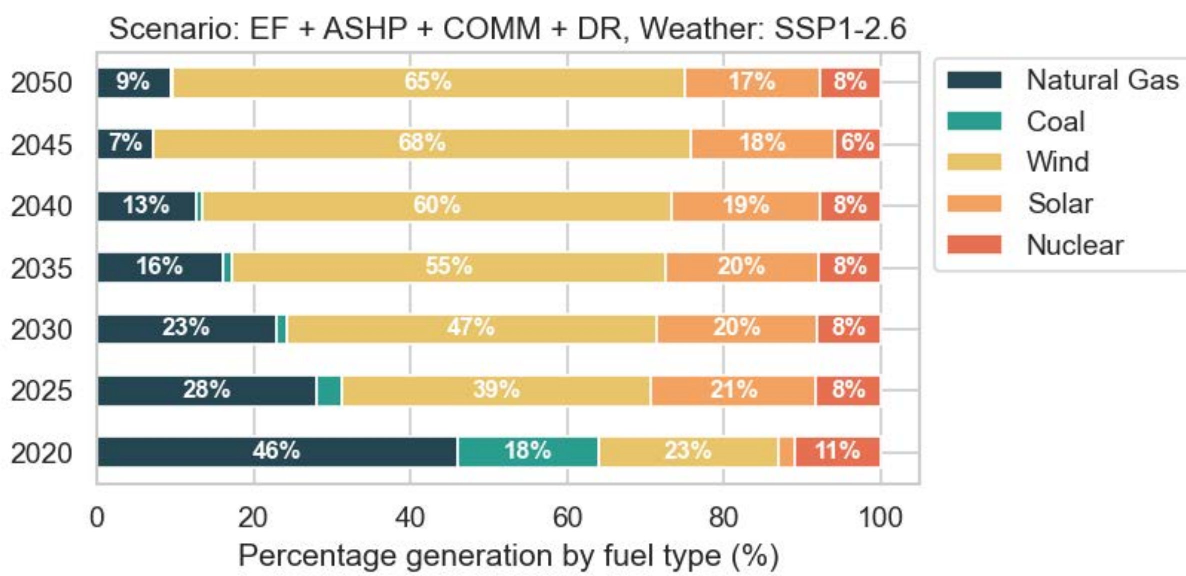


Figure 86: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM + DR scenario assuming SSP1-2.6 weather.

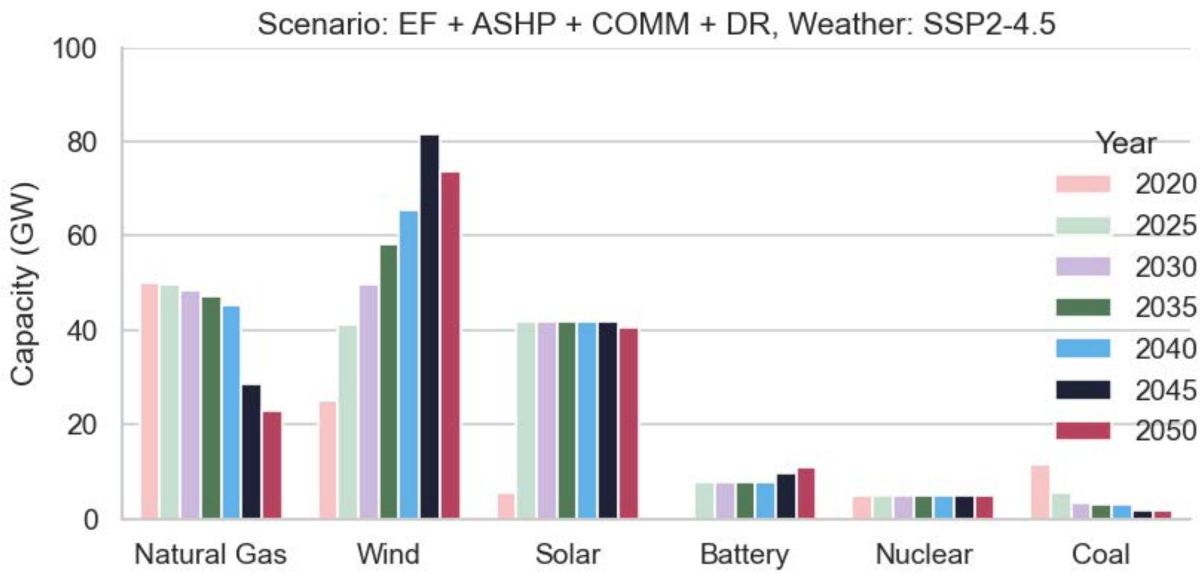


Figure 87: Figure showing the total capacity for various generation types in the ERCOT grid grid in the EF + ASHP + COMM + DR scenario assuming SSP2-4.5 weather.

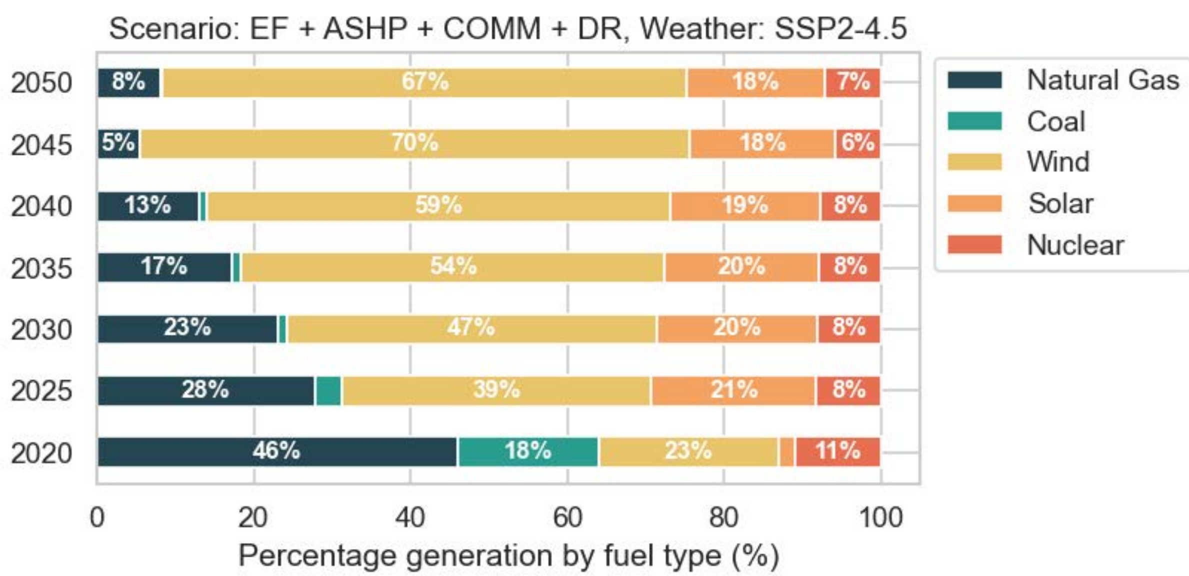


Figure 88: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM + DR scenario assuming SSP2-4.5 weather.

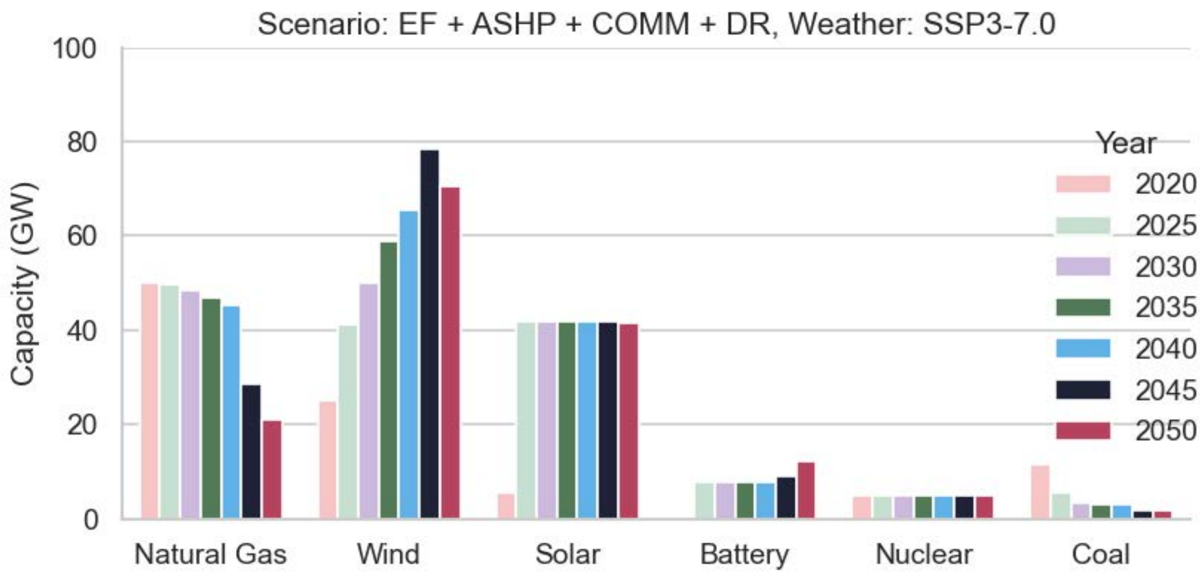


Figure 89: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM + DR scenario assuming SPP3-7.0 weather.

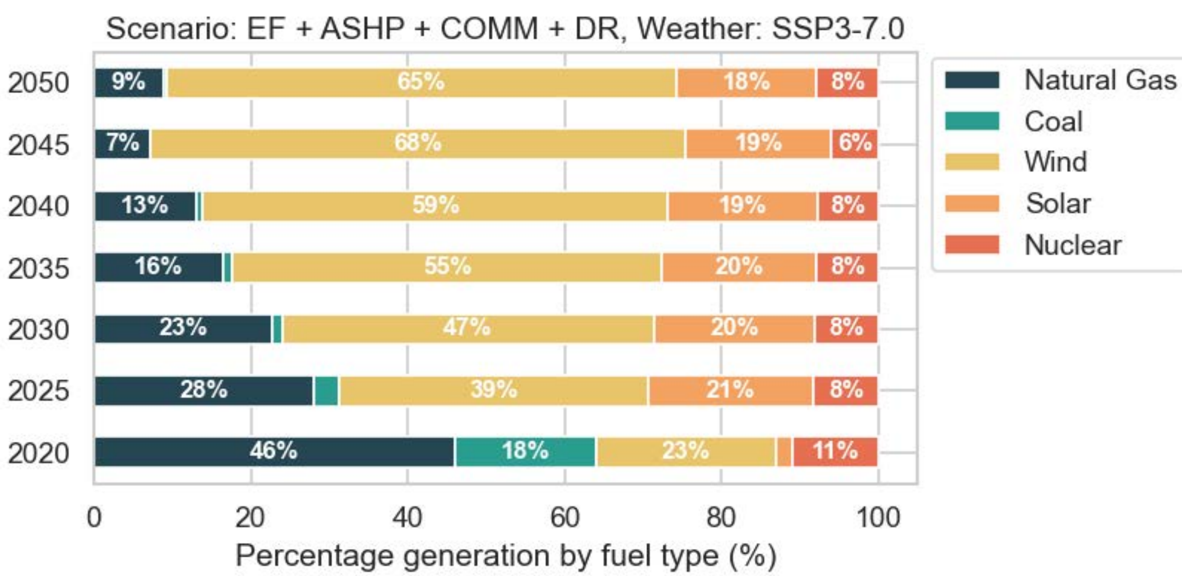


Figure 90: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM + DR scenario assuming SPP3-7.0 weather.

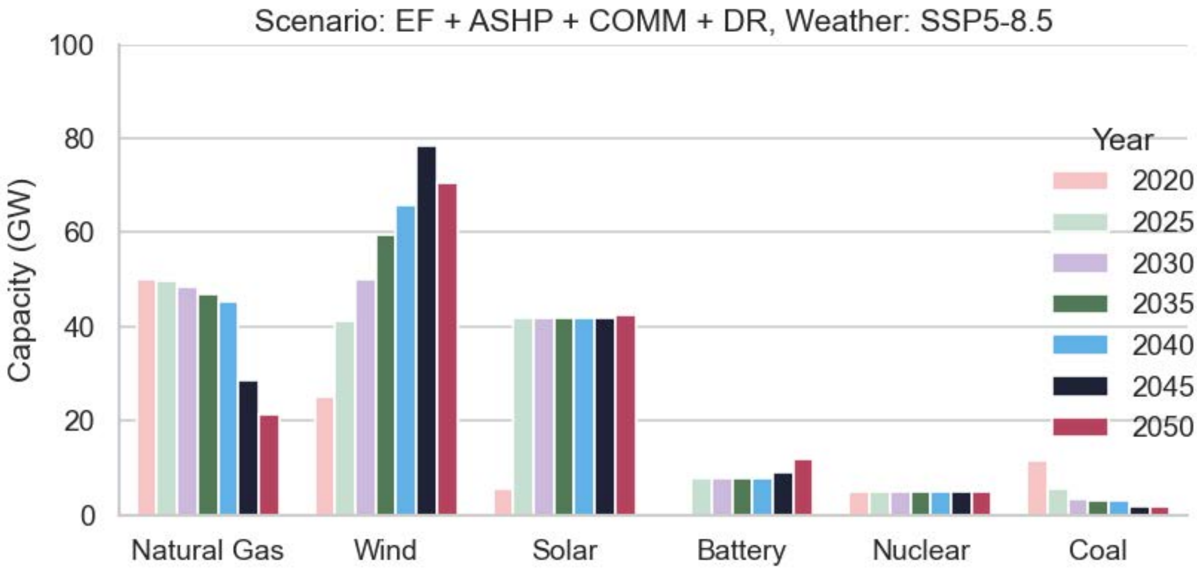


Figure 91: Figure showing the total capacity for various generation types in the ERCOT grid in the EF + ASHP + COMM + DR scenario assuming SSP5-8.5 weather.

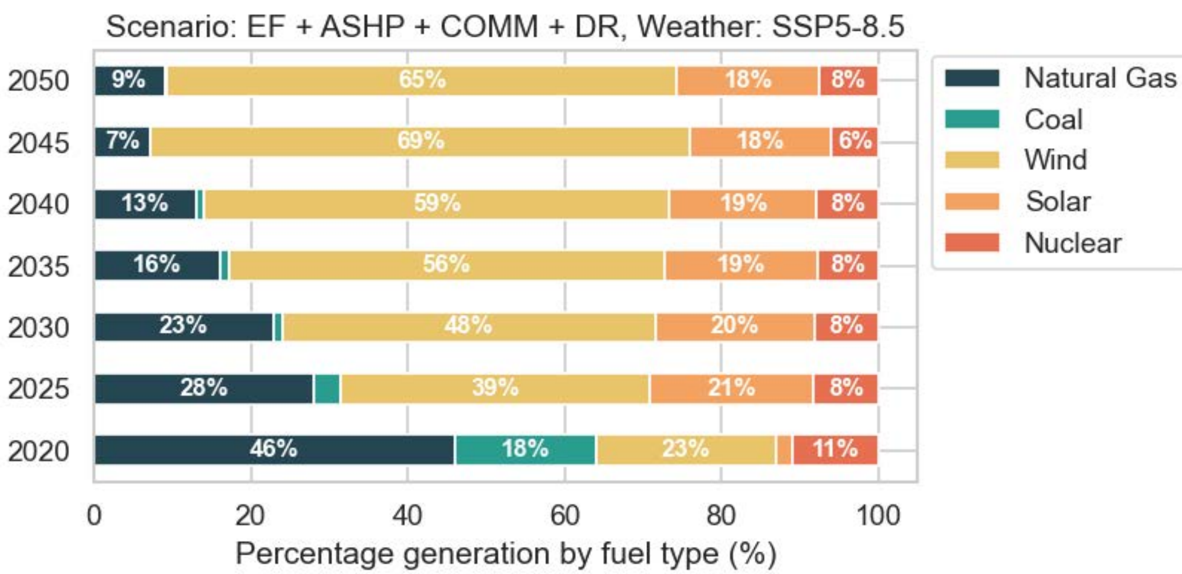


Figure 92: Figure showing the amount of energy generated by fuel type in the ERCOT grid from 2020 (actual) to 2050 in the EF + ASHP + COMM + DR scenario assuming SSP5-8.5 weather.

Appendix B

Sample Texas Energy Utility Energy Efficiency Programs

CenterPoint Energy

CenterPoint Energy offers a number of residential energy efficiency programs which include: the Coolsaver A/C tune-up that is offered to customers to improve the efficiency of their air conditioning units by up to 27%. A Coolsaver qualified technician also identifies ways to improve the efficiency of the air conditioner (A/C) and implement any recommended improvements. This program is available for use every 5 years. The other programs are upgrading HVAC systems with potential rebates, investing in a smart thermostat (installation of ENERGY STAR® certified smart thermostats leads to a $50 instant rebate), insulation assessments, and discounted LED lighting [49].

CenterPoint Energy's agencies in action program provides whole house energy weatherization upgrades to income-eligible housing. To qualify for this program, the home must be at least 16 years old and the annual household income has to meet the low-income guidelines or receive benefits from a public assistance program [50].

The Residential Standard Offer Program (RSOP) and Hard-To-Reach Standard Offer Program (HTR) are other programs offered by CenterPoint energy aimed at achieving cost effective reduction in peak demand on the electric grid. These programs offer incentives to a wide range of contractors, service companies, community agencies and other organizations for the installation of energy efficiency retrofit projects within the CenterPoint Energy electric territory. The HTR program specifically targets households with incomes at or below 200% of the federal poverty guidelines [51].

AEP Texas

AEP Texas also offers the Coolsaver A/C tune-up program as well as the Hard-to-Reach Standard Offer Program which was specifically developed for households with incomes at or below 200% of the federal poverty guidelines or who participate in approved government programs. This specific program helps residential customers reduce energy consumption through the installation of energy efficiency measures in their homes. These measures include home envelope, interior energy usage, and air conditioning system measures. The Targeted Low-Income Program is another program designed to cost-effectively reduce energy costs and energy consumption for AEP Texas' low-income customers. Not-for-profit community agencies identify eligible customers, conduct home assessments, and arrange for the installation of weatherization and energy efficiency measures in households with incomes in the stipulated federal poverty guidelines range. Other programs offered by AEP that improve grid resilience are: the SMART Source^{SM} Solar PV Program, which is designed to help customers meet a portion of their energy needs with solar electric systems by offsetting the initial cost of a solar energy system installation and AEP's Residential Standard Offer Program, which provides incentives to participating contractors for the installation of eligible energy efficiency services and products in residential customers' homes [52].

Oncor

Oncor offers incentives for projects like home energy efficiency insulation, low-income weatherization, and solar photovoltaic systems for households. The incentives for residential solar photovoltaic systems are dependent on the size, azimuth and other factors of the installed system. Homeowners need to install solar photovoltaic systems with an energy storage back up system to qualify for these incentives. Oncor's New Homes Program provides incentives to homebuilders who construct ENERGY STAR® certified or Zero Energy Ready Homes. These incentives help achieve customer energy and cost savings [53].

CPS Energy

CPS Energy's SaveNow - Save for Tomorrow Energy Plan (STEP) was launched in 2009 to reduce the community's energy demand by 771 Megawatts (MW) by 2020. This goal was exceeded one year ahead of time and under budget. In 2019, STEP saved CPS customers enough energy to power over 104,000 homes and provided 680 annual jobs. There are a number of rebates included in STEP such as: Wi-Fi thermostat rewards, home energy rebates for central air, heat and pool pumps, attic insulation, window A/C units, and solar PV [54].

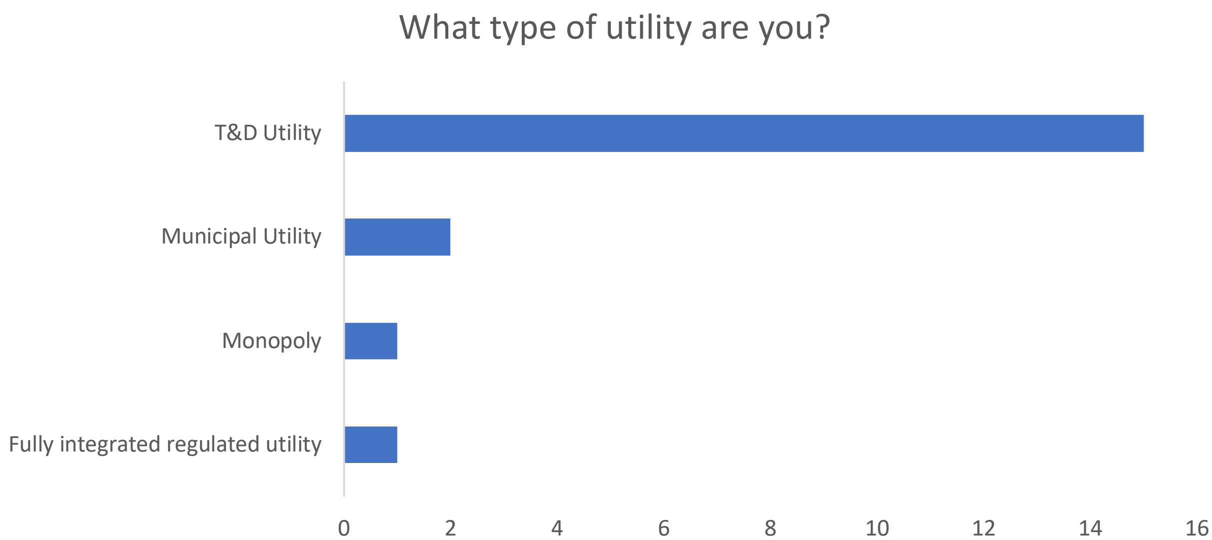
TNMP

TNMP offers both a high-performance homes program and Residential and Hard-to-Reach Standard Offer Programs (Res/HTR SOPs). The former provides financial incentives for constructing energy-efficient homes that meet current program guidelines. It also promotes the construction and certification of high-performance and ENERGY STAR® certified new homes. The Res/HTR SOPs were developed by TNMP to provide incentives to suppliers of energy services. The primary objective of these programs is to achieve cost-effective reduction in summer peak demand, winter peak demand, and annual energy consumption for TNMP's residential and hard-to-reach customers. Additionally, the TNMP low-income weatherization program provides incentives for the installation of energy efficiency upgrades in the single-family homes of low-income customers [55].

Appendix C

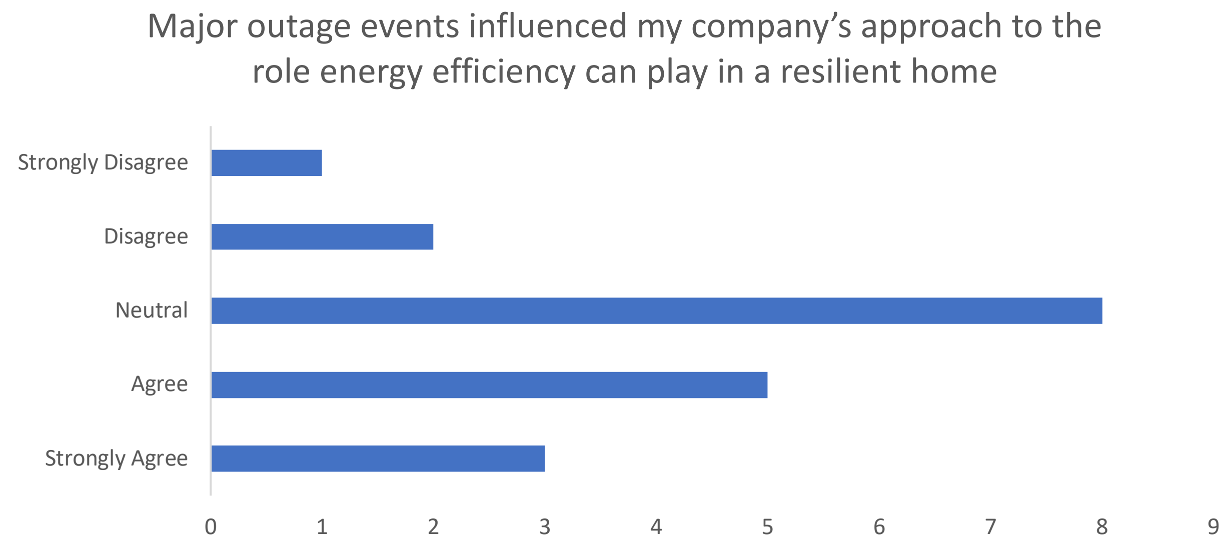
Utility Survey Responses

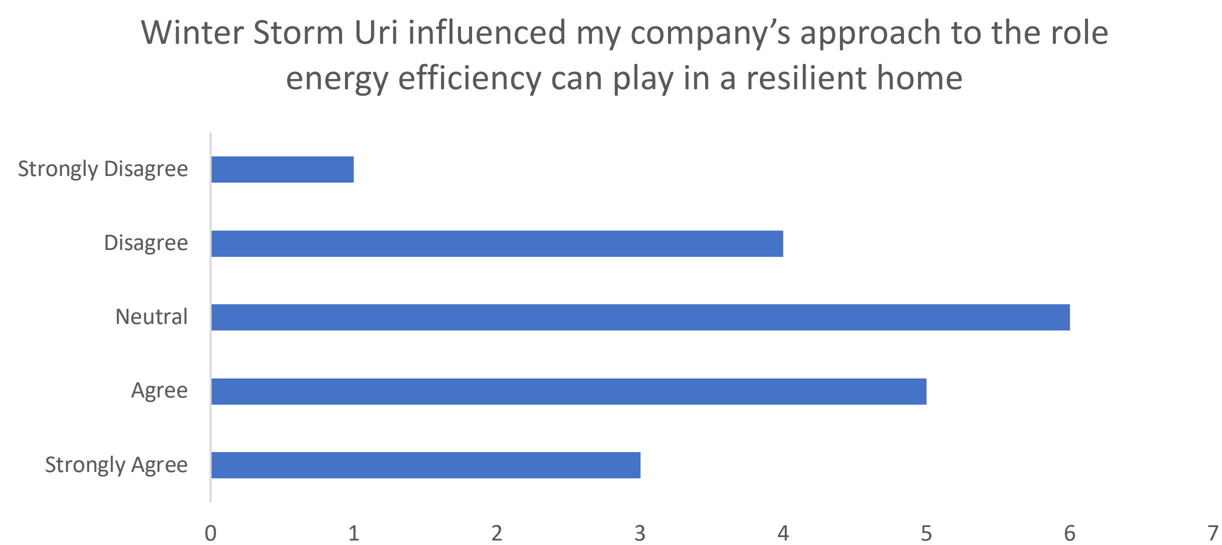
There were 19 survey responses. Most respondents (15) were Transmission & Distribution utilities. An additional four respondents were from a municipal utility, monopoly, or fully integrated regulated utility.



Outage Events

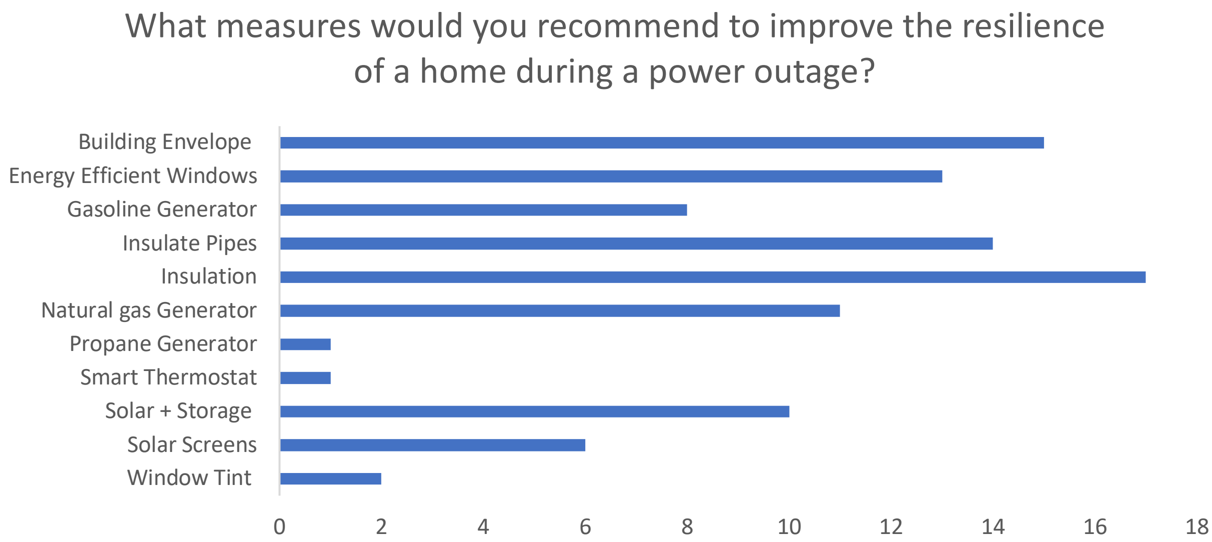
Utility professionals were asked about their experiences with power outages and Winter Storm Uri. Many agree that their company was influenced by major outages, including Winter Storm Uri. Eight of nineteen respondents agree or strongly agree that a major outage event influenced their company's approach to the role energy efficiency can play in home resilience. The same number of respondents indicated Winter Storm Uri influenced their company's approach to energy efficiency. Eight of nineteen respondents indicated a neutral response to the idea that their company was influenced by a major outage event, and six respondents indicated influence from Winter Storm Uri. Three respondents disagree or strongly disagree that their company's approach to energy efficiency was influenced by a major power outage, and five respondents disagree or strongly disagree that their company's approach was influenced by Winter Storm Uri.



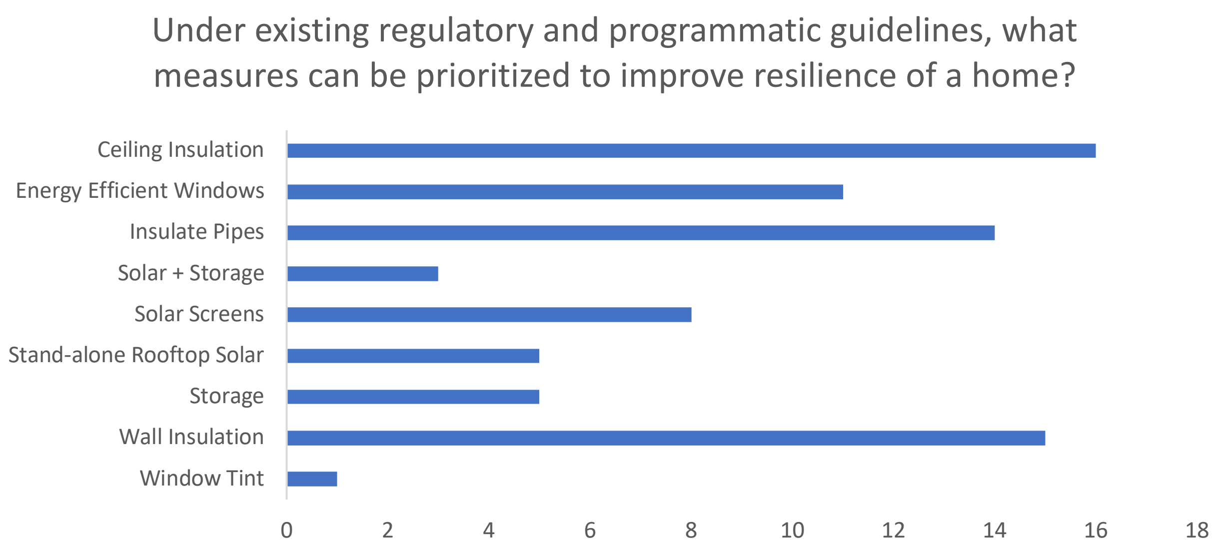


Home Resilience

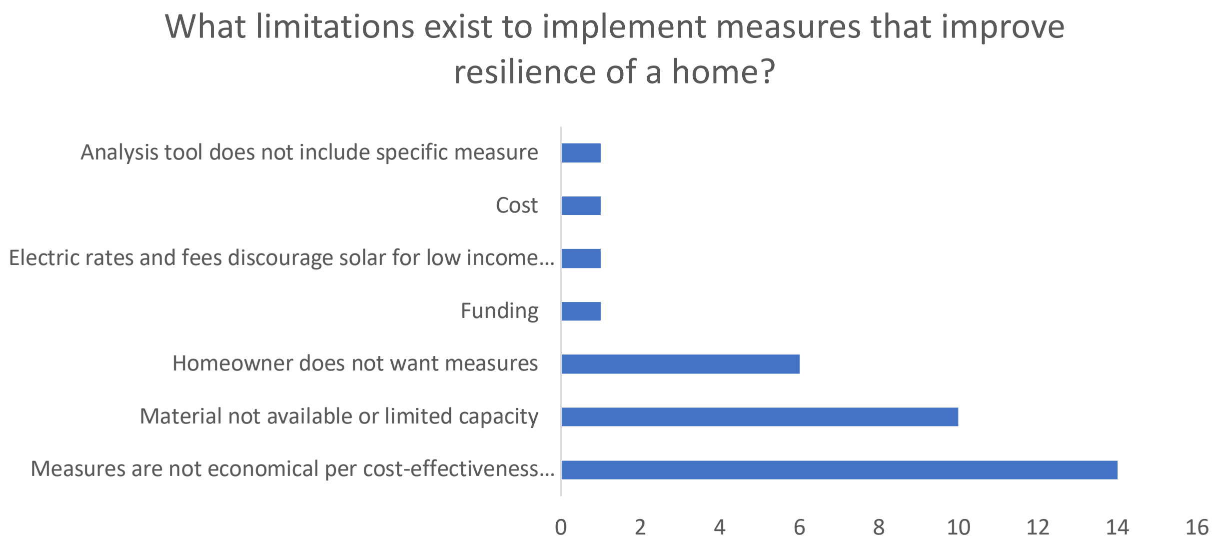
Utility professionals were asked about measures to improve home resilience. The most recommended strategy is insulation. A majority of respondents recommend improving the building envelope, replacing windows with energy efficient windows, and insulating pipes. While windows are a priority, fewer respondents recommend solar screens (6) or window tint (2). Additionally, a majority of respondents recommend adding onsite power, such as a natural gas generator and/or solar+storage to the home; fewer respondents recommend a gasoline or propane generator. Smart thermostats were not highly recommended by utility respondents. While smart thermostats are good for energy efficiency, program professionals do not see them as providing added resilience.



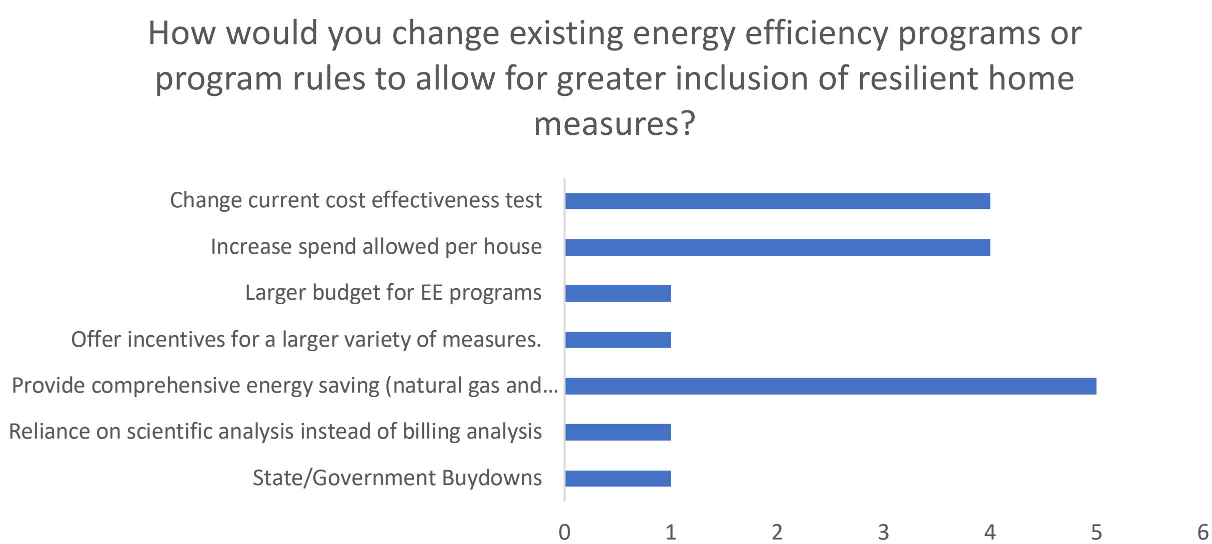
Under existing regulatory and programmatic guidelines, a majority of respondents recommend prioritizing ceiling, wall, and pipe insulation and energy efficient windows. Fewer respondents recommend solar screens (8) and window tint (1). Some respondents recommend solar or storage with fewer respondents recommending both solar and storage.



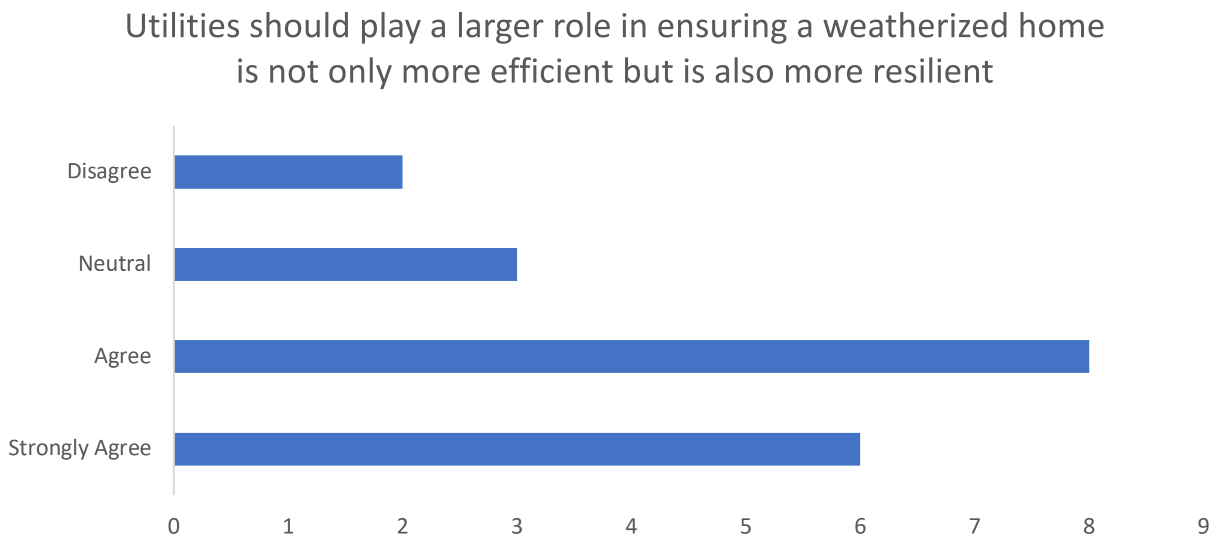
Utility professionals were asked about limitations to implementing home resilience measures. Most respondents indicated that the cost-effectiveness methodology limits their ability to implement measures that improve home resilience. Two respondents elaborated on their responses. One indicated residential customers want air infiltration but can no longer receive it due to changes to the TRM and duct efficiency savings. Another respondent indicated if resilience measures do not show energy savings on paper, incentive dollars cannot be used. Additionally, most respondents indicated material availability limits their ability to implement measures. One third of respondents indicated homeowner interest limits the ability to implement measures.



Respondents were asked about how they would change existing energy efficiency programs or rules to allow for more measures that could make homes resilient. Responses varied with no majority reply. However, a plurality of respondents recommended providing comprehensive energy savings, including both natural gas and electricity. Four respondents agreed that increasing spending per house and changing the current cost-effectiveness test would be needed to allow greater inclusion of resilient home measures.

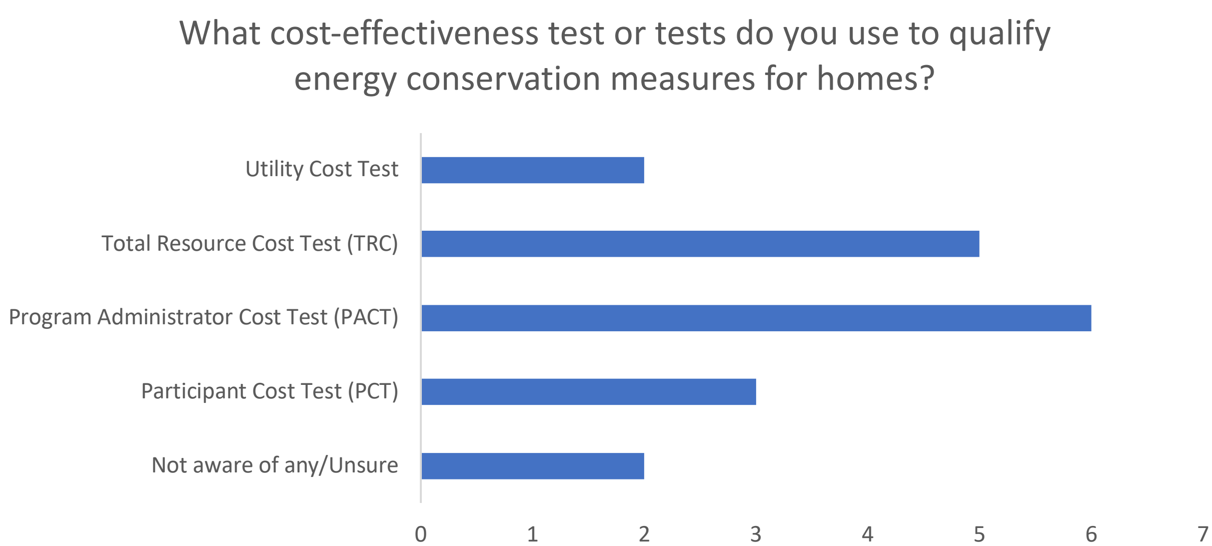


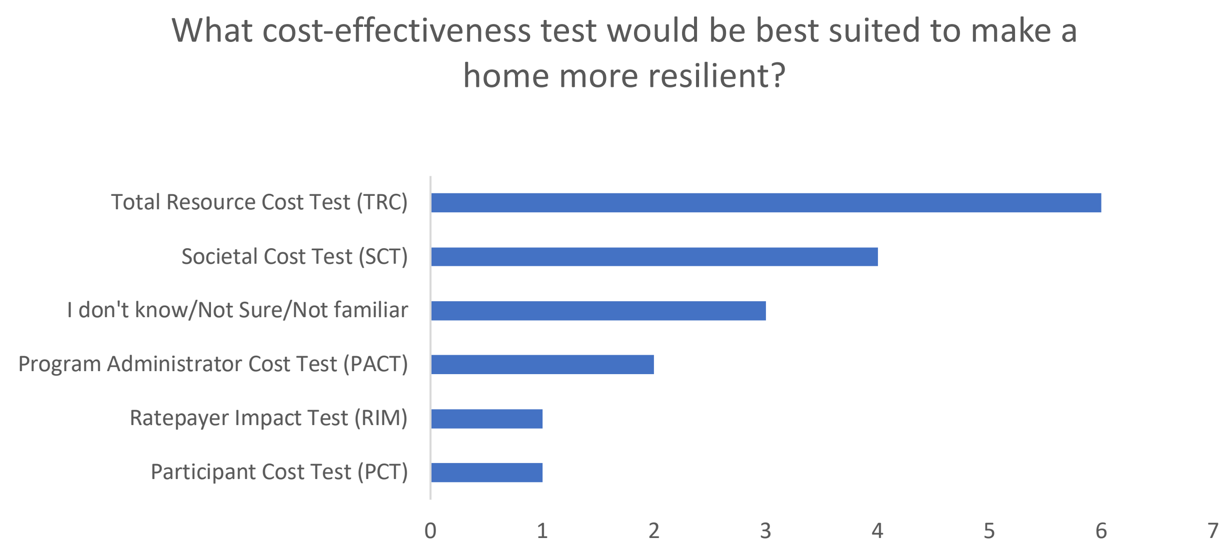
Utility professionals were asked their sentiment on the statement "Utilities should play a larger role in ensuring a weatherized home is not only more efficient but is also more resilient." Most respondents agree or strongly agree with this idea. Only two respondents disagreed, both from T&D utilities.



Cost Effectiveness Tests

A variety of cost-effectiveness tests are utilized by utilities to administer weatherization and efficiency or conservation measures. Utility professionals were asked which tests they use to qualify energy conservation measures. Utilities rely on different tests. Two utility respondents were unaware of the cost effectiveness tests provided. No one test is used by a majority of respondents, but a plurality of respondents use the Program Administrator Cost Test. When asked what cost effectiveness test would better support more resilience-related measures a plurality of respondents prefers the Total Resource Cost Test.

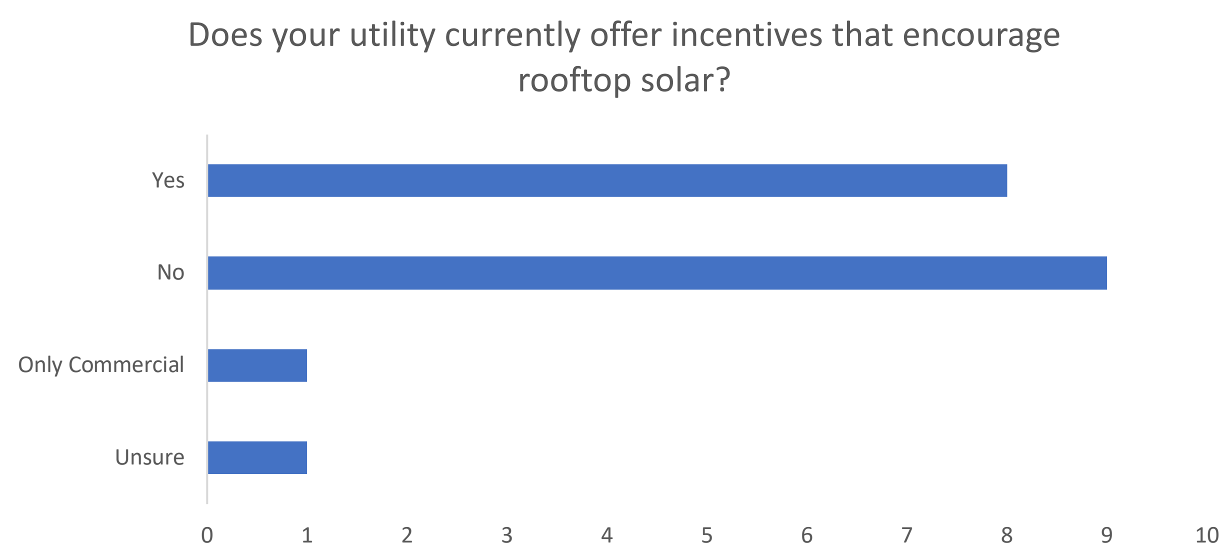




Utility Incentives

Respondents from utilities that do not offer a solar incentive indicated that the cost of solar is too high or the payback too long even with an incentive. One respondent indicated that solar is seen as generation, but they are not able to own generating assets. Another respondent indicated that residential solar is a conflict of interest for the utility.

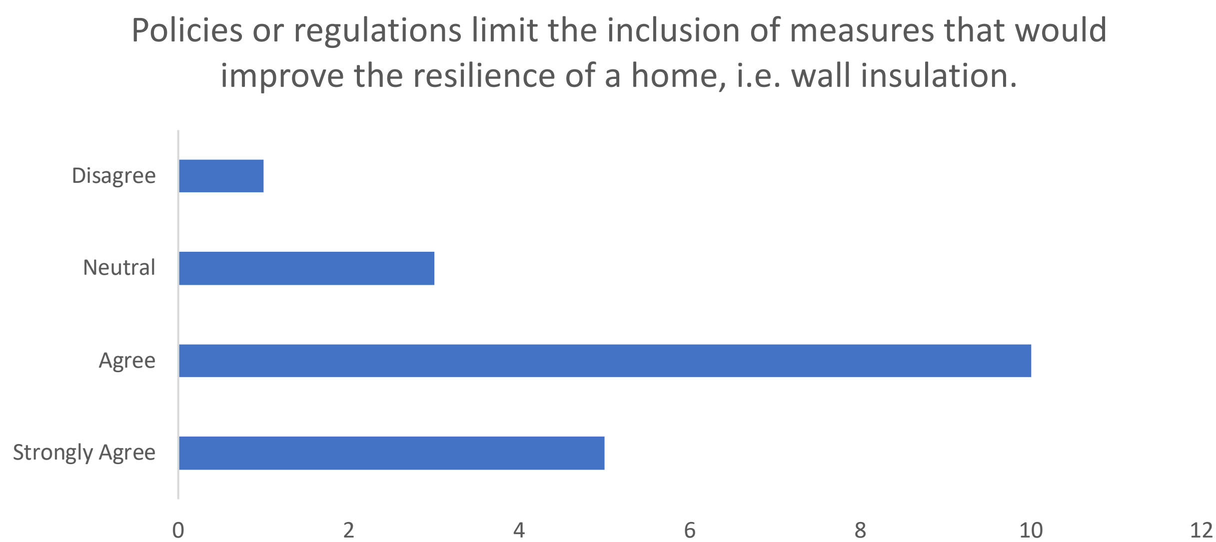
Respondents from utilities that do offer solar incentives indicate that customers are interested in the incentive (3), that it is cost effective for the utility (1), and that it provides energy savings (1). Municipal utilities indicated renewable incentives fit their priorities for renewable energy (2).

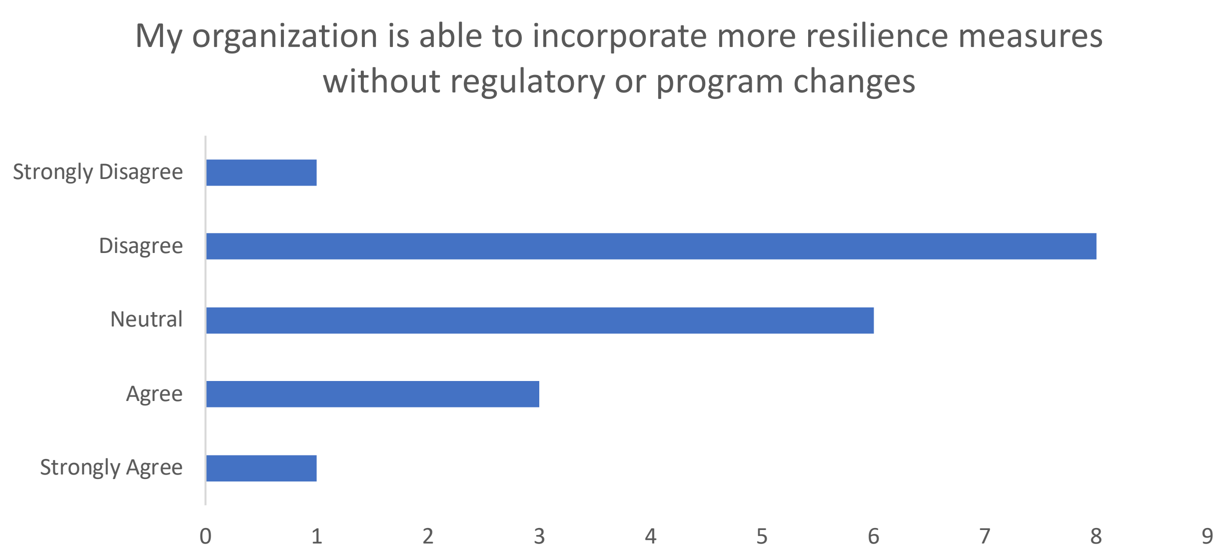


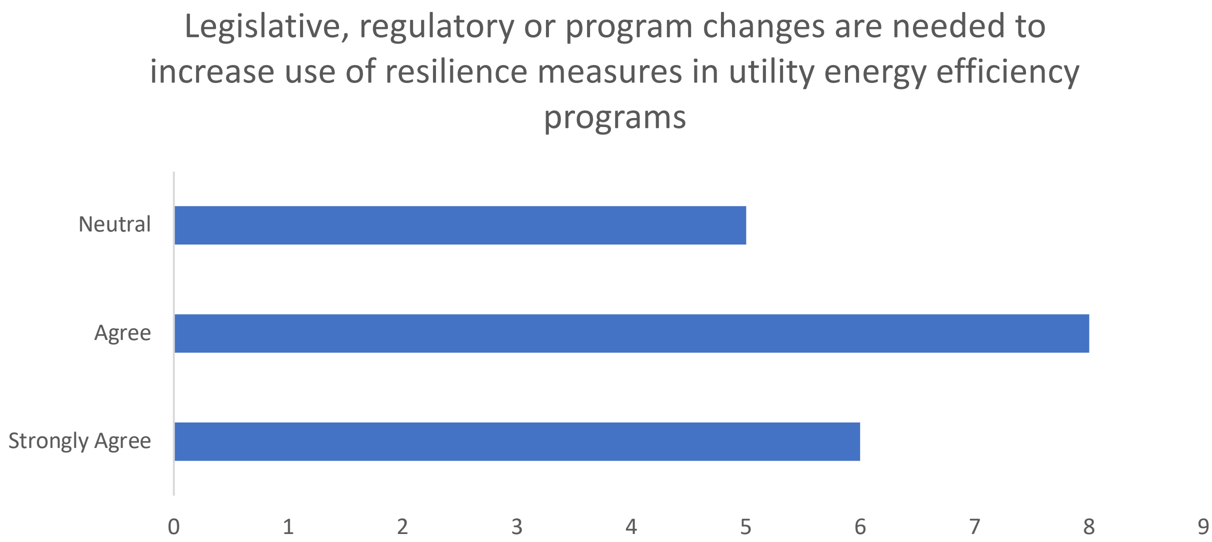
No utilities offer incentives that encourage battery storage. Responses indicated some utilities might see batteries as an emerging market, too young or too expensive for their incentives to be cost-effective. One response questioned how savings could be claimed. Two respondents indicated regulations prevented assistance for battery storage as it is considered generation, but they are not able to own generating assets. Two other respondents indicated approval for battery incentives may begin soon.

Utilities and Policies or Regulation

Utility professionals were asked about the influence of policy, regulation, and legislation on use of energy efficiency or weatherization programs for home resilience. Most respondents agree or strongly agree that policies or regulations limit the inclusion of measures that would improve the resilience of a home; disagree or strongly disagree that their organization is able to incorporate more resilience measures without regulatory or program changes; and agree or strongly agree that legislative, regulatory, or program changes are needed to increase use of resilience measures in utility energy efficiency programs.






Legislative, regulatory or program changes are needed to increase use of resilience measures in utility energy efficiency programs
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Appendix D

1. General Model Summary: Capacity Expansion Modeling in Switch

The analysis for this project is completed using the capacity expansion model called, "SWITCH" [56].

A capacity expansion model is an optimization program that makes decisions about the operation and construction of power plants, transmission lines, and other electric grid assets. It accomplishes this at two different time scales:

- Short Time Scale: the model dispatches the power plant fleet so that electricity generation and electricity demand are balanced for each hour of the simulation.
- Long Time Scale: the model builds new power plant capacity to 1) provide enough power plants so that electricity generation and demand can be balanced in future years, and 2) enable the composition of the power plant fleet to evolve in ways that minimize the total system cost.

The model solves for the Short and Long Time Scales simultaneously to meet the modeling objective. The objective for this model is to minimize the net present value of all investment and operation costs. Thus, the model will

- dispatch power plants in the Short Time Scale so that the least expensive power plants are turned on first, to balance the hourly generation and demand at the lowest possible cost, and
- build new power plants if the upfront investment cost of constructing those power plants will reduce the total net present value by reducing the cost of the Short Time Scale power plant operation during future time periods.

This objective is subject to a number of constraints and input variables. For example, power plant operational characteristics, fuel prices, power plant construction costs, renewable energy generation profiles, transmission capacity, and many other variables described in the following sections constrain the model's solution.

"Switch" is a unique grid planning model that is built using capacity expansion modeling theory. Switch is developed and maintained by Professor Matthias Fripp at the University of Hawaii and has been in development since 2012. It is an open source model built on the Python programming language. For more details about the model, its validation, calibration, and equations, see [56].

2. Time Series

Because a capacity expansion model operates at both Short and Long Time Scales, it must use simplified time series so that the model is tractable and can be solved. For example, a capacity expansion model that solves a 2020-2050 scenario will <u>not</u> solve for all 8,760 hours of all 30 analysis years. Instead, it will use a few representative days for each year, and a few representative years for the whole 30-year time scope.

In this model, we use seven representative days and six representative years.

2.1. Representative Days

This model uses 7, 24-hour periods to represent the annual electricity market. Those 24-hour periods include:

- Summer and winter peaks: we use the 24-hour profile of the day with the greatest instance of hourly system demand in the summer and winter. These peak time series are scaled up to represent 6 of 365 days for each model year each.
- Winter average: we use the average 24-hour profile of February to represent 28 of 365 days for each model year.
- Summer average: we use the average 24-hour profile of November, December, and January to represent 30 of 365 days for each model year.
- Winter season average: we use the average 24-hour profile of February to represent 89 of 365 days for each model year.
- Summer season average: we use the average 24-hour profile of May, June, August, and September to represent 117 of 365 days for each model year.
- Summer season average: we use the average 24-hour profile of May, June, August, and September to represent 117 of 365 days for each model year.
- Shoulder season average:

2.2. Representative Years

The model simulates these seven representative days a total of six times each. Each of the four time periods represents a 5-year span: 2020-2025, 2025-2030, 2030-2035, 2035-2040, 2040-2045, and 2045-2050.

For each of these 5-year time periods, we average the input values across those years. For example, the natural gas price for the 2020-2025 time period equals the average of the 2020, 2021, 2022, 2023, and 2024 forecasted natural gas prices.

3. Generator Data

Our model represents each individual power plant in the ERCOT system. To parameterize each of these power plants, we compile data from a variety of sources as outlined below.

3.1. ERCOT Capacity Demand and Reserve Report, 2018 [57]

Twice a year, ERCOT releases a report that includes some data for all of the operating generators in the ERCOT market. We use this report to gather data on each existing generator’s:

- capacity,
- construction year, and
- county.

3.2. Emissions & Generation Resource Integrated Database (eGRID), 2018 [58]

eGRID is maintained by the EPA and contains information about the existing U.S. power plant fleet. We use it to gather data on each ERCOT generator's:

- fuel type, and
- technology type.

3.3. Annual Technology Baseline (ATB), 2019 [59]

The ATB is published annually by NREL and contains a set of assumptions and futures to inform electric sector analyses in the U.S. The data provides operational and cost characteristics for different types of generators projected from 2018-2050. We use it to gather data for each generator's:

- scheduled outage rates,
- forced outage rates, and
- fixed operation and maintenance cost.

We also use the ATB to provide the following data for characterizing new generators:

- capital cost of construction,
- fixed operation and maintenance cost,
- heat rate, and
- roundtrip efficiency for battery charge/discharge cycles.

3.4. Garrison Dissertation, 2014 [60]

In addition to the sources above, which are used broadly for modeling the U.S. power sector across many different regions, we also refer to the dissertation of Dr. Jared Garrison, which contains data compiled specifically for modeling the ERCOT region. Those data include the following.

3.4.1. Heat Rates

Heat rates for existing generators are calculated by diving each generator's monthly fuel consumption by its monthly electricity generation. These data come from the US EIA 923 database. We average these monthly heat rates over multiple years to approximate each generator's full load heat rate.

3.4.2. Startup Costs

Startup costs for existing and new generators are based on data from the Power Plant Cycling Costs report. This report lists startup cost for cold, warm, and hot startups. For the ERCOT power plants, the startup costs for each generator type were selected based on whether that generator type tends to startup from warm or cold conditions.

3.4.3. Min Up and Down Time, Min Output, and Variable Operation & Maintenance Costs

These characteristics come from the assumptions that ERCOT uses for the capacity expansion model used to create the ERCOT Long Term System Assessment report. Based on conversations with different stakeholders, Garrison updated some of these original data for a few of the generator types.

3.5. Coal Retirements

Based on age, the majority of coal plants are expected to retire in Texas by 2035, we force coal retirements for any coal plants that have been operating for 43 years or longer. This requirement has the following impact on overall coal capacity:

- 2018: 13.1 GW
- 2020-2025: 11.5 GW
- 2025-2030: 5.5 GW
- 2030-2035: 3.3 GW
- 2035-2040: 3.0 GW

4. Wind and Solar

4.1. Profiles

We use hourly wind and solar generation profiles for hundreds of sites around ERCOT. These generation profiles were developed by AWS TruePower for ERCOT and are available for public download [61].

The hourly profiles are simulated using historical weather data. A generation profile is created for each existing wind and solar site in ERCOT along with many potential sites where wind and solar capacity have not yet been installed.

For developing future wind capacity, we let the model expand the capacity of simulated sites (modeled at a hub height of 90m) and existing sites with hub heights of 80m or greater. For existing sites with hub heights below 80m, we use their profiles to represent existing wind generation resources available for dispatch, but do not let the model expand their capacity. For counties without existing or simulated wind generation, we average the profiles of sites with similar wind resources in neighboring counties.

For developing future solar capacity, we let the model expand the capacity of the simulated sites. Texas solar resources [62] generally improve as one travels west. We observe this trend in the capacity factors of the simulated solar sites, but not consistently in the capacity factors of the existing solar sites. Thus, we use the profiles of existing sites to represent existing solar capacity resources available for dispatch, but do not let the model expand their capacity.

4.2. Site Limits for Wind and Solar Capacity

Since wind and solar plants require a significant amount of real estate, we limit the amount of wind and solar development that the model can build in each Texas county.

For solar, we assume single-axis tracking arrays built at a density of 30 MW/km^2 (77.7 MW/mi^2). [63]

For wind, we use the appendix data from [64] to divide the total Texas wind capacity by the total developed land area of that wind capacity to get a density of 7.14 MW/mi^2.

We then multiply these development densities by the square mileage of land in each county that is available for development[17]. The result is the maximum amount (MW) of wind and solar capacity that could be built in the developable land in each county.

The wind limit is, on average, 6.5 GW per county. But that capacity can only be realized if all of the county's available land area has suitable wind resources. However, in most counties, the wind resource quality varies across the county's geography. To account for this, we use data from [65] to estimate the amount of land in each county that has wind resources with wind speeds of 7.0-7.5, 7.5-8.0, and 8.0+ m/s. We use those estimates to cap the amount of capacity that each wind site may develop, depending on its capacity factor.

The solar limit is, on average, 70.4 GW per county. In practice, this solar limit never constrains the model. Thus, we assume that, because of its density, solar development has little impact on wind development—i.e., if a county builds many GW of solar capacity, this requires a relatively small amount of land and we assume that it does not meaningfully diminish the county's wind capacity limit.

4.3. Annual Limits for Wind and Solar Capacity Growth

Wind and solar development are also limited by materials supply chains, manufacturing capabilities, and construction capabilities. To capture this, we impose an annual limit on how much wind and solar can be built in the model.

For both wind and solar, we establish a baseline limit on GW/year that can be installed. Then, assuming that these limitations will increase with GDP, we scale the installation limits up according to the forecasted Texas GDP growth through 2050 [66].

For the baseline wind limit, we take data on annual wind development in Texas from 2009-2019 [67] [68]. We take the average of these numbers—1.45 GW/year—as the baseline for the wind development limit.

We assumed the same deployment rate for utility-scale solar. However, we also assumed that all projects that have current interconnection agreements in the EROCT GIS system would be built on-time.

4.4. Land Lease Rates for Wind and Solar

The fixed operating cost of each wind and solar site varies depending on which county it is built in. To accomplish this, we first compile a lease rates for rangeland, native pasture, and hunting leases in 33 Texas regions [69]. Then we normalize those lease rates, multiply them by wind and solar lease costs from [70], and assign them to the counties contained in each region. Note that wind land lease costs vary from 1,100 to 24,500 $/MW-year with an average of 8,960 and solar land lease costs vary from 630 to 14,400 $/MW-year with an average of 8,960.

[17] Personal communication with the University of Texas at Austin Bureau of Economic Geology.

We then use these land costs to adjust the fixed operation and maintenance costs from section 3.3 by:

- for wind sites: subtracting the average wind land lease cost from the wind FOM. Then adding back the county-specific wind land lease cost.
- for solar sites: because the ATB does not include solar land lease costs in its solar FOM, we simply add the county-specific solar land lease cost to the ATB FOM.

4.5. Tax Credits

5. Transmission

As electricity travels from region to region it incurs losses and must not exceed the capacity of the transmission lines. The model can increase the capacity of the existing transmission lines by paying the capital cost to build new lines.

5.1. Losses

We assume losses of 1% per 100 miles of transmission. This aligns with the assumption used by the National Renewable Energy Laboratory's ReEDS model [71]—a capacity expansion model of the continental United States.

5.2. Regions and Capacities

The model comprises 16 regions with transmission capacity between many of the regions' borders. The regions and transmission locations were determined using geographic transmission data from the Department of Homeland Security [72].

5.3. Construction Cost

Transmission construction costs are based on data from the Competitive Renewable Energy Zones (CREZ) project—a large-scale transmission construction project carried out in ERCOT from 2008-2013. We use a transmission construction cost of about 2300 $/MW-mile (1,430 $/MW-km) as described in [73].

6. Fuel Prices

Fuel price data come from the EIA's 2020 Annual Energy Outlook (AEO) [74]. This report contains future projections out to 2050 of energy consumption, emissions, and fuel prices. We use the

- forecasted AEO coal prices for our model's subbituminous coal prices,
- forecasted AEO coal prices plus 0.72 $/mmBtu for our model's lignite coal prices, and
- forecasted AEO natural gas prices for our model's natural gas prices.

The lignite prices are increased by 0.72 $/mmBtu so that the average of the forecasted 2020-2030 prices equal the average of the historical 2015-2020 Texas lignite prices [75].

7. Financial

The Switch model uses an interest rate and discount rate for various financial calculations. We assume a discount rate equal to a weighted average cost of capital (WACC) of 7.17% and an interest rate of 6.01%. These align with the assumptions of the NREL ATB [59].

Appendix E

This appendix includes one already published paper [6] for this project as well as another that has been submitted for publication.

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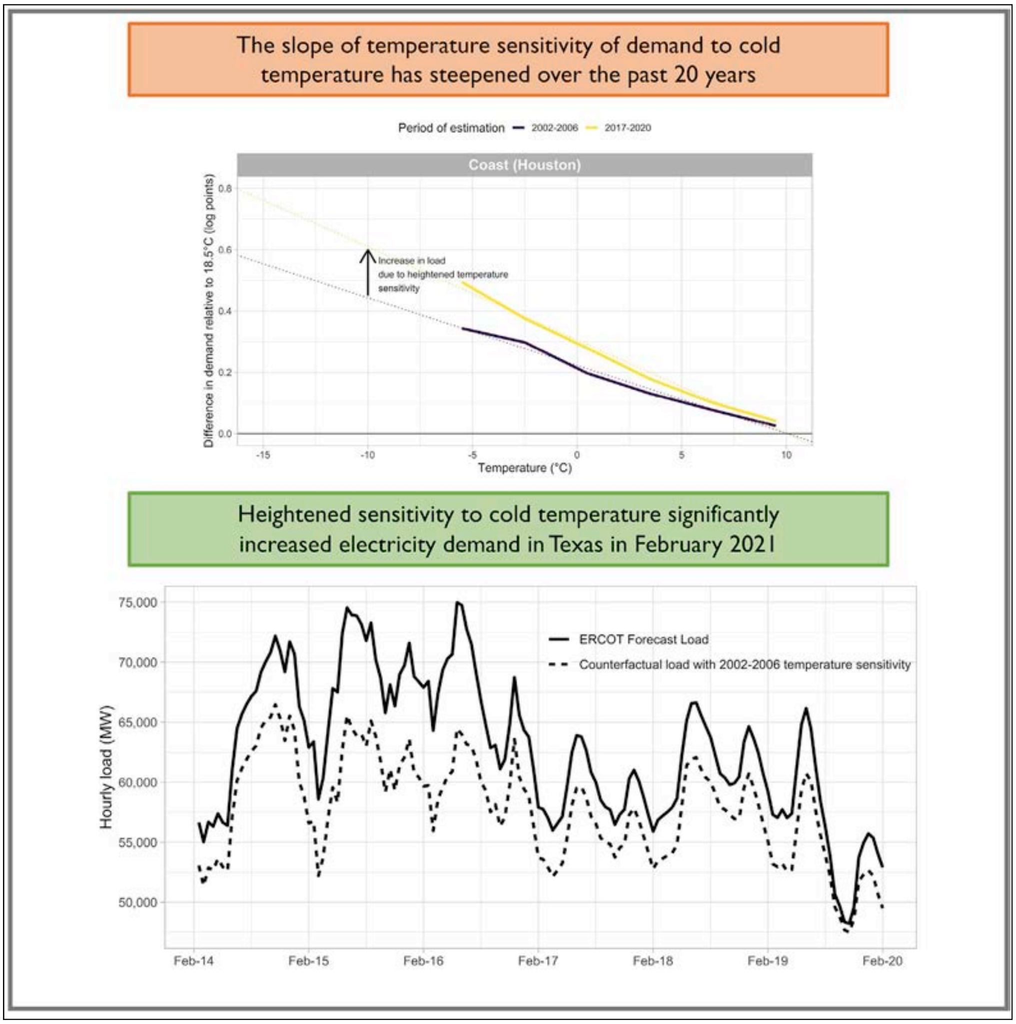
Article

Changing sensitivity to cold weather in Texas power demand



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Highlights

Texas power demand sensitivity to cold temperature has steepened over the past 20 years

Heightened sensitivity of demand exacerbated the February 2021 Texas outage event

Average demand was 8% higher due to greater cold temperature sensitivity

This has implications for regions that are electrifying heating

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April 15, 2022
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Article

Changing sensitivity to cold weather in Texas power demand

Blake Shaffer,[1,3,*] Daniel Quintero,[1] and Joshua Rhodes[2]

SUMMARY

We estimate the effect of heightened temperature sensitivity on electricity demand in Texas during the February 2021 blackout event. Using 20 years of hourly data, we estimate the relationship between temperature and electricity demand; finding demand has become more responsive to cold temperatures over time. This is consistent with the fact electric heating has similarly increased over the past 20 years in Texas. We find during the February 2021 event, average electricity demand was 8% higher, and approximately 10,000 MW higher during the peak hour, than it would have been had temperature sensitivity remained unchanged at early 2000s levels. Our results highlight that Texas's increased sensitivity to cold weather extremes is not limited to the supply side, but the demand side as well. These findings have implications to other regions that are seeking to reduce carbon emissions through the electrification of heating.

INTRODUCTION

In February 2021, the extreme cold weather from Winter Storm Uri strained the Electric Reliability Council of Texas (ERCOT) power grid to the brink. Over the course of five days, roughly 12 million Texans were left in the dark. In total, nearly 1,000 GWh of firm electric load was shed (not served) as rolling blackouts were enacted to avoid a complete system-wide loss of power. The human health and safety toll was large, with an official estimate of 246 people dying, unprotected in the cold, and ancillary infrastructure, such as water systems, breaking down (Texas Department of State Health Services, 2021). The economic damages from the storm are expected to exceed $100 billion US dollars (Accuweather, 2021).

In the aftermath, much of the focus has been on the supply side of Texas' power market. The question of which fuel type was "most at fault" became politicized; conversations about the interdependence of electricity and natural gas systems, and the need to winterize both, echoed the same conversations from only ten years ago, during the last "great freeze" in Texas; and ERCOT's unique "energy-only" market design was called into question as to whether it led to insufficient levels of reliability. All important questions that will undoubtedly be studied and discussed for years to come.

Far less focus, however, has been placed on the demand side. What is clear is just how large electricity demand in the region was, leading up to the blackout event. In ERCOT's seasonal assessment of resource adequacy for Winter 2020/21, the planned winter peak demand—the basis upon which ERCOT determines whether they have sufficient capacity to meet demand—was 57,699 MW (ERCOT, 2020). An extreme peak load scenario was included in the assessment at 67,208 MW based on a repeat of the 2011 cold weather event in the state. On Sunday February 14, a typically off-peak day, ERCOT set a record peak winter load of 69,692 MW at 8p.m., with forecasts calling for a peak exceeding 76,000 MW for the coming midweek cold snap, before load shed eventually negated such levels from occurring. In terms of daily average load, Sunday February 14th 2021 was the highest daily average load in ERCOT history (see Figure S1).

In this paper, we ask the question: Has electricity demand in Texas become more sensitive to cold weather? And, if so, how much higher was electricity demand during the February event due to heightened temperature sensitivity? We motivate this investigation by noting that over the past 15 years the share of Texan households using electric heat has risen from 52% to 61% (U.S. Census Bureau, 2004; 2019). Given a higher reliance on electricity for heating, it would be reasonable to expect Texas electricity demand to be more sensitive to cold weather events today than in the past. Thus, at the cold temperatures observed in

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February 2021, even if not the most intensely cold on record (Doss-Gollin et al., 2021), the electrification of heating stands to push electricity demand higher than would previously have been expected.

We answer this question using nearly 20 years of hourly historical weather and electric load data to estimate the temperature responsiveness of electricity demand across each of ERCOT's eight weather zones, and, importantly, how these temperature response functions have changed over time. In doing so, we are able to calculate the increase in electricity demand during the cold temperatures observed in February 2021 that is attributable to an increasingly cold-weather-responsive demand. We find heightened temperature responsiveness accounts for an average increase in overall ERCOT demand over the outage period of roughly 8% (absent the load shed), and slightly more than 10,000 MW of additional load during the peak hour event on the morning of February 16, than it would have been absent the increase in cold-weather sensitivity. This is after controlling for annual trends, such as population and overall load growth.

These findings highlight Texas' changing sensitivity to cold weather events. The extreme events in 2021 were not only challenging for the supply side of power generation but also from additional temperature sensitivity to cold weather resulting in greater demand for electricity than would have been the case only a decade ago. We discuss implications to other regions seeing increased electrification of heating as a pathway to net-zero emissions.

Several studies have examined the temperature responsiveness of electricity demand, but largely in the context of increasing temperatures due to climate change (Isaac and van Vuuren, 2009; De Cian and Wing, 2017; Wenz et al., 2017; Auffhammer et al., 2017). Others have considered the adaptive effect of increased air conditioner penetration, leading to heightened responsiveness of electricity demand to higher temperatures (Davis and Gertler, 2015; Rivers and Shaffer, 2020). There is comparatively very little research on the effect of greater electrification of heating in terms of altering the temperature sensitivity of power demand in the domain of cold temperatures. This analysis seeks to fill that knowledge gap.

RESULTS

Temperature response functions

We begin by estimating the relationship between temperature and electricity demand, conditioning on other non-temperature factors of demand, as per (Equation 1) in the method details section (below). We do so separately for each ERCOT weather zone, using data from 2002 through 2020. Data from 2021 are excluded from the estimation because (a) we want to avoid the confounding effect of the load shed during the outage event, and (b) the year fixed effect would be problematic given the partial year containing below-average temperatures (i.e. winter period only). We plot the temperature response functions, for each region, in Figure 1. These functions show the expected percentage difference in electricity demand for a given prevailing temperature relative to 18.5°C (approx. 65 °F).

The temperature response functions exhibit their familiar U-shape, consistent with the existing literature, highlighting that electricity demand increases as temperature deviates in both directions from a neutral point, resulting in either heating or cooling load. The steepness of each side of the temperature response function represents the sensitivity to cold and hot temperatures, respectively.

Next, we re-estimate temperature response functions by zone, but this time doing so using separate five-year periods. This allows us to follow the evolution of temperature responsiveness over time. The results are shown in Figure S2 in the supplemental information.

In two of the eight zones, namely the West and Far West, we see a flattening of the temperature response functions over time. It appears load is becoming less sensitive to temperature in these two zones. This is consistent with the continued growth in less temperature-sensitive electrified oil and gas development in west Texas (ERCOT, 2018). A neutral result is observed in the North Zone, with little change over time. Whereas, in the remaining five zones (North Central, Coast, South Central, South, and East), the temperature response functions all steepen in the most recent period of estimation relative to the oldest period, reflecting a heightened sensitivity to cold temperatures. These zones represent the bulk of ERCOT's load, or roughly 90% of the total, and thus increases in temperature sensitivity in these regions overwhelmingly drive total ERCOT electricity demand.

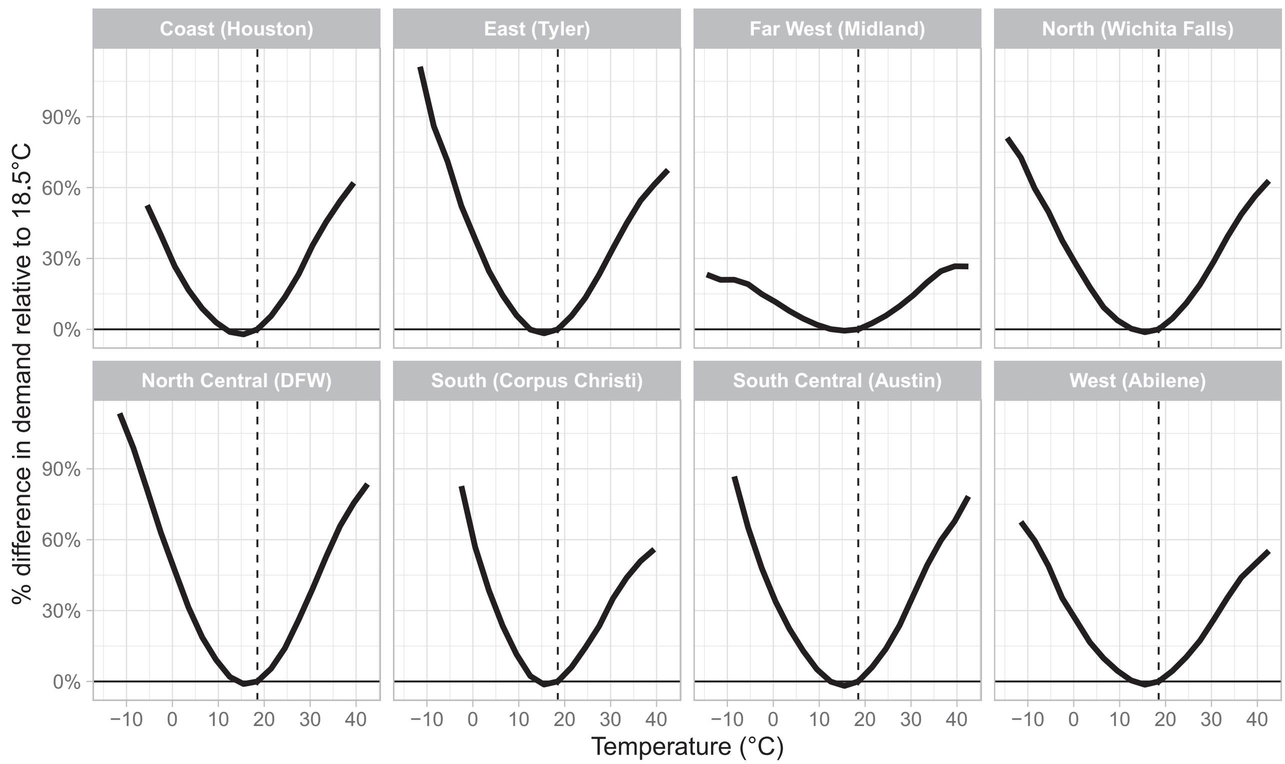

Figure 1. Temperature response functions by ERCOT weather zone; all years

Plotted are the estimated regression coefficients representing percentage difference in demand for each respective temperature bin relative to 18.5°C. Note, the coefficients, estimated in log points, have been converted to percentage change by the following: $\beta_{percentchange} = \exp(\beta_{estimated}) - 1$. For small changes, $\beta_{percentchange} \approx \beta_{estimated}$.

Projecting the effect of changing sensitivity to cold temperatures

We now use the estimated temperature response functions to answer the originally proposed question: by how much greater was electric load during the February 2021 event due to heightened cold temperature sensitivity? To do so requires extrapolating the estimated temperature response functions over a range of temperatures outside the domain of temperatures used in the estimation process above.

Figure 2 plots the temperature response functions for one zone—the Coast Zone—over the domain of cold temperatures (i.e. below 10°C), for the oldest (2002–2006) and newest (2017–2020) periods. From the figure, we see that a linear approximation is a strong fit for the temperature response functions over this range of temperatures, with demand differences measured in log points. Extrapolating this linear fit into the colder temperatures observed in February 2021 allows us to calculate the additional electric load due to heightened temperature sensitivity. The linear assumption has been used by Auffhammer et al. (2017) and Rivers and Shaffer (2020), among others, to extrapolate beyond the domain of estimated temperatures. In those examples, it was for extrapolating to higher temperatures due to climate change. While certainly some non-linearities could exist in the relationship beyond the currently estimated temperature domain, our concern here is the difference between two temperature response functions, and thus it would be *changes in non-linearities over time* that would be the confounding factor.

We repeat the analysis displayed in Figure 2 for all zones. As previously mentioned, in the majority of zones, heightened temperature sensitivity results in more load than would have been the case with 2002–2006 sensitivity; whereas in a few zones, notably smaller ones, the opposite is true. Summing across all zones results in a clear and significant increase in load due to temperature sensitivity.

Figure 3 plots hourly total ERCOT load over the period of February 14–19, 2021. The actual ERCOT forecast load is represented by the solid line. This is the load forecast by ERCOT had there not been firm load shed

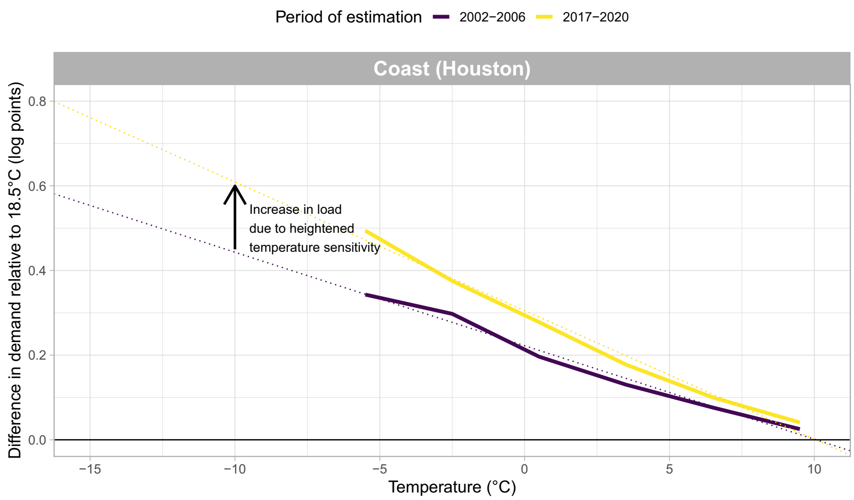

Figure 2. Temperature response function for Coast zone; below 10°C

Plotted are the estimated regression coefficients representing percentage difference in demand for each respective temperature bin relative to 18.5°C Note, for visualizing this linear fit, the coefficients are shown in their estimated log points.

(i.e. blackout) events. The dashed line is the estimated counterfactual load had ERCOT had the temperature sensitivity observed in 2002–2006 as compared to 2017–2020. It is constructed by taking the ERCOT load forecast and adding the difference between the estimated load deviation based on 2002–06 temperature responsiveness and 2017–20 responsiveness, both evaluated at the observed hourly temperatures in February 2021.

At the peak, during the morning of February 16, our model indicates heightened temperature responsiveness accounts for an additional 10,800 MW of demand. Across the entire period of the February 2021 blackouts, we estimate heightened temperature sensitivity increases total forecast load by 8%, as compared to what load would have been had temperature sensitivity remained at 2002–06 levels. This effect is after controlling for annual trends, such as population growth, and is purely indicative of increased temperature sensitivity.

DISCUSSION

Temperature sensitivity to cold weather in most parts of Texas has increased over the past 20 years. We estimate this increased sensitivity resulted in an additional 8% average load during the extreme cold of February 2021 than would have occurred had temperature responsiveness remained at 2002–06 levels. At the same time, electric heating shares have risen from 52% to 61% of households, an increase of roughly two million homes, in the state of Texas over the past 15 years (U.S. Census Bureau, 2004; 2019). We stress that lack of data preclude us from making causal claims as to the link between electric heating and the observed change in sensitivity—the relationship we observe is strictly correlative—however, our results are consistent with results from a simulation study (White and Rhodes, 2019) that shows increased electric heating in the Texas's residential sector leading to larger winter electricity peaks.

Our results highlight Texas's heightened susceptibility to extreme cold weather events, a fact much discussed on the supply side of the power market, but with little conversation as to shifts in demand. The prevalence of inefficient electric resistance heat may play a large role in Texas's temperature responsiveness to cold weather; a shift toward more efficient heat pumps could prove valuable in reducing energy needs during cold weather events, though at extreme temperatures these efficiency gains may be reduced. Our findings suggest more work on the direct link between changes to heating equipment and electricity demand should be undertaken to improve the accuracy of load forecasts to incorporate changing relationships.

Our results also have broader implications to other regions, in the United States and globally, increasing their electrification of space heating. As efforts to achieve net-zero emissions increase, and electrification

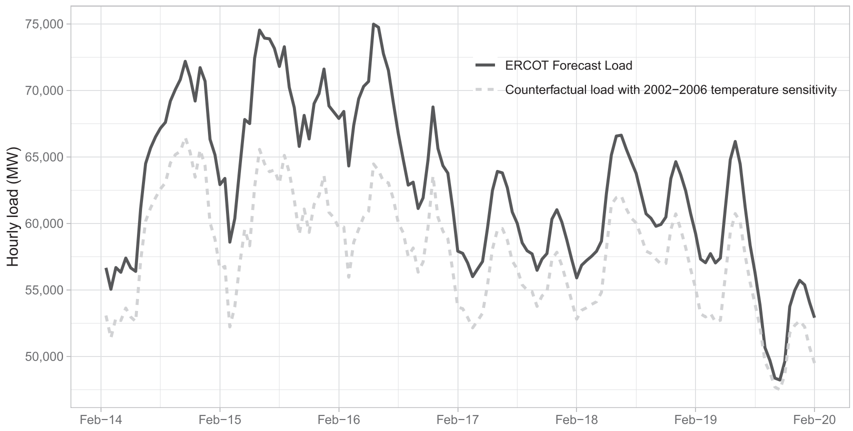

Figure 3. Load forecast and counterfactual load with 2002–2006 temperature sensitivity

ERCOT forecast load is used in place of actual load as the firm load shed truncated desired demand. The counterfactual hourly load is calculated by taking the ERCOT load forecast and adding the difference between the estimated load deviation based on 2002–06 temperature responsiveness and 2017–20 responsiveness, both evaluated at the observed hourly temperatures in February 2021.

of space heating plays a central element in many pathways, this paper emphasizes the need to incorporate the increased prevalence of electric heating to rethink temperature-demand relationships. Heightened temperature sensitivity will require greater capacity in cold weather conditions than previously considered to ensure electric reliability.

Limitations of the study

This study provides a historical correlative analysis of the relationship between cold weather and electricity demand in Texas, and how it has changed over time. Two limitations of the current analysis are (1) its usefulness for prediction, and (2) its lack of causal link as to the underlying mechanism that is changing the relationship between cold temperatures and electricity demand. We discuss each in turn.

Prediction

We control for changes over time using a year fixed effects approach. This approach means we do not need to arbitrarily specify the factors that affect demand over time, allowing the year fixed effect to flexibly subsume all potential factors. However, it limits our study's usefulness for prediction purposes. An alternative approach would be to include a large set of conditioning variables, such as population growth, GDP, industrial composition, etc., allowing for predictions of future demand by incorporating assumptions on the future level of these variables. The trade-off with such an approach is potential omitted-variable bias and the requirement of assumptions around the value of these conditioning variables for prediction.

Causal mechanism

We highlight the associative link between the increased sensitivity of electricity demand to cold weather and the increased use of electric space heating in Texas. However, this link is purely correlative, as we have insufficiently granular data to perform a proper causal analysis using panel data. A potentially fruitful area of future research would be to use household-level electricity data, along with a household-level panel on space heating, to properly estimate the causal link between electric space heating adoption, cold temperature, and electricity demand.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
    - Lead contact
    - Materials availability

- Data and code availability
- METHOD DETAILS
  - Temperature response function estimation method

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.104173.

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AUTHOR CONTRIBUTIONS

Shaffer: Conceptualization, Methodology, Investigation, Formal Analysis, Writing-Original Draft, Writing-Review & Editing, Visualization, Project Administration; Quintero: Data Curation, Investigation, Formal Analysis, Writing-Original Draft, Writing-Review & Editing; Rhodes: Data Curation, Investigation, Writing-Original Draft, Writing-Review & Editing, Funding Acquisition

DECLARATION OF INTERESTS

Joshua Rhodes consults for various companies that operate in the Texas electricity market through his firm IdeaSmiths LLC. 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. Shaffer and Quintero declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Weather Data	National Oceanic and Atmospheric Administration (NOAA)	https://www.ncdc.noaa.gov/cdo-web/datatools/lcd/
Electric Load Data	Electric Reliability Councilof Texas (ERCOT)	http://www.ercot.com/gridinfo/load/load_hist/
Heating Type Data	United States Census Bureau	https://data.census.gov/cedsci/
Software		
R	R for Statistical Computing	https://www.r-project.org

RESOURCE AVAILABILITY

Lead contact

Further information and requests for comment should be directed to and will be fulfilled by the lead contact, Blake Shaffer (blake.shaffer@ucalgary.ca).

Materials availability

Not applicable.

Data and code availability

- All data used in the analysis (electric load, weather, and heating type) have been deposited at https://github.com/blakeshaffer/ercotproject/ and are publicly available as of the date of publication.
- All original code used in the analysis has been deposited at https://github.com/blakeshaffer/ercotproject/ and is publicly available as of the date of publication.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

METHOD DETAILS

In this method details section, we first describe the key data sources used in the analysis and present summary statistics. This is followed by a detailed description of our temperature response function estimation method.

Temperature response function estimation method

We estimate the temperature response function, i.e. the relationship between temperature and electricity demand, using hourly load and temperature data, separately across each ERCOT Weather Zone. Specifically, we run eight separate regressions, one for each Zone (z), regressing the logarithm of hourly load (y_t) on hourly temperature variables (T_{tb}) and a rich set of date and time fixed effects (X_t):

$$\log\left(y_{t;z}\right) = \sum_b \beta_{b;z} T_{bt;z} + \theta_z X_{t;z} + \epsilon_{t;z}, \ \forall z \qquad \text{(Equation 1)}$$

For the temperature variables, T_{btz}, we use binned temperature dummies in 3°C increments, across the range of observed temperatures in Texas from 2002 through 2021. For example, the variable $T_{8-11^\circ C,tz}$ receives a '1' if the temperature in hour t in zone z falls in bin b = (8 to 11°C], and a '0' otherwise. The omitted bin is the one centred around 18.5°C (roughly 65 °F), and thus the interpretation of each bin's coefficient is the log difference in demand between temperatures in the respective bin as compared to demand when temperature is 18.5°C. For small changes, the log difference in demand can be roughly interpreted as the percentage change in demand, i.e. 0.1 ≈ 10% change. This approach allows for a flexible relationship between temperature and demand. An alternative approach, also used in the literature, is to use heating and cooling degree days, essentially the absolute difference between recorded temperature and a "neutral" baseline of 18.5°C. We use temperature bins as it avoids the requirement to impose an arbitrary nadir to the non-linear temperature-demand relationship. Any temperature bins with less than 10 hourly observations are dropped due to imprecision of their estimates.

X_t is a vector of date and time fixed effects that are predictable factors of demand. These include dummy variables for year, month, day of week, and hour of day. Year fixed effects control for annual load growth trends. This flexibly controls for levels shifts in demand due to time-varying factors, such as population and prices. As a robustness check, we also run regressions using population-normalized demand as the dependent variable. We do so by taking the logarithm of demand per capita in kWh, using hourly load data and annual county-level population data aggregated to the ERCOT weather zone. While year fixed effects remove level shifts in average demand due to population growth and other factors, population-normalizing the demand variable allows us to check if sensitivity differs more or less in extreme conditions due to population changes. We find no significant difference in the results. Monthly fixed effects control for predictable seasonality in electricity demand independent of weather. Day of week controls for typical weekday/weekend fluctuations in demand, and hour of day controls for predictable patterns of the intraday shape of demand. We include interactions between month and hour, and between day of week and hour, to reflect that the hourly demand profile differs both seasonally and across different days of the week. Our identifying assumption is that after conditioning on these predictable factors of demand, the variation in shocks to electricity demand (ε_t) are uncorrelated with temperature. Because of the high resolution of fixed effects covering key drivers of electricity demand that we include in our specification, as well as year fixed effects making our identification based on within-year variation, we believe that this specification should successfully identify the short-run effect of temperature on consumption. We note, also, that this method follows that of many papers in the existing peer-reviewed literature (Auffhammer et al., 2017; Wenz et al., 2017; Rivers and Shaffer, 2020).

After performing this estimation separately for each zone over all years in the dataset, we then separately estimate the temperature response functions using data by zone in 5 year increments to determine the evolution of temperature response functions over time. Specifically, a steepening of the left hand side of the temperature response function—the region of cold temperatures—indicates heightened cold temperature sensitivity and thus for comparable cold temperatures, electricity demand is expected to be higher, all else equal.

Observations of winter and summer electric load growth in ERCOT and its implications for future resource planning

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Abstract

This analysis quantitatively compares the evolution in summer and winter peak demands in the Electric Reliability Council of Texas (ERCOT) service area over the 25-year period of 1997 to 2021 using a linear regression analysis. Weather data for the days in which peak demand occurred were also compiled to investigate the relationship between peak heating and cooling loads and ambient temperature. We found that the summer peak demand growth has been generally stable and approximately linear with time. The stable summer peak load is likely a consequence of fairly constant temperatures observed on summer peak demand days. Conversely, the winter peak demand growth has been less consistent, varying much more around the broader trend. This phenomenon is likely a consequence of high residential electrical heating load on winter peak demand days, which saw temperatures that varied widely from the mean value. Thus, resource planners in ERCOT should place less certainty on winter peak demand projections and an increased level of winter preparedness on both the supply and demand sectors appears warranted for resource planners in all regions. In light of the high penetration of electrical heating equipment in Texas relative to other regions, these events might foreshadow future resiliency challenges that other regions will face as electric heating equipment is deployed in place of boilers or furnaces for decarbonization purposes.

Keywords: Electrification, Distributed Energy Resources, ERCOT, Demand Response, Energy Security and Risk Assessment, Peak Demand

1. Introduction

Heating is the largest global energy end-use (about 50% of energy demand) ahead of transport (29%) and electricity (21%). Forty-six percent of this heat energy is consumed within buildings for space and water heating and to a lesser extent, cooking [1]. Natural gas is used to heat 60% of U.S. households in cold and very cold climates and 47% of U.S. households overall [2], thereby releasing significant greenhouse gases from leaks and combustion-related emissions. Consequently, the electrification of heating is a typical component of decarbonization efforts [3, 4], and bans on fossil-fuel based space heating equipment have already been administered in numerous cities to achieve this end [5–7]. As a result, electrical heating equipment as a portion of global heating technology sales for residential and service buildings has been steadily increasing for years, a trend that is expected to continue through the next decade [8]. These factors have led regional electric grid operators to anticipate a large expansion of space heating demand from the residential and commercial sectors and predict a potential switch from a traditional summer peak to a winter peak [9, 10]. Questions remain about how this new source of electricity demand will affect electric grid operations. In particular, how will grid resiliency be impacted by the electrification of space heating? How will electric load for residential space heating, which already drives winter peak power demand [11], and is sensitive to severe weather events, be affected by climate change?

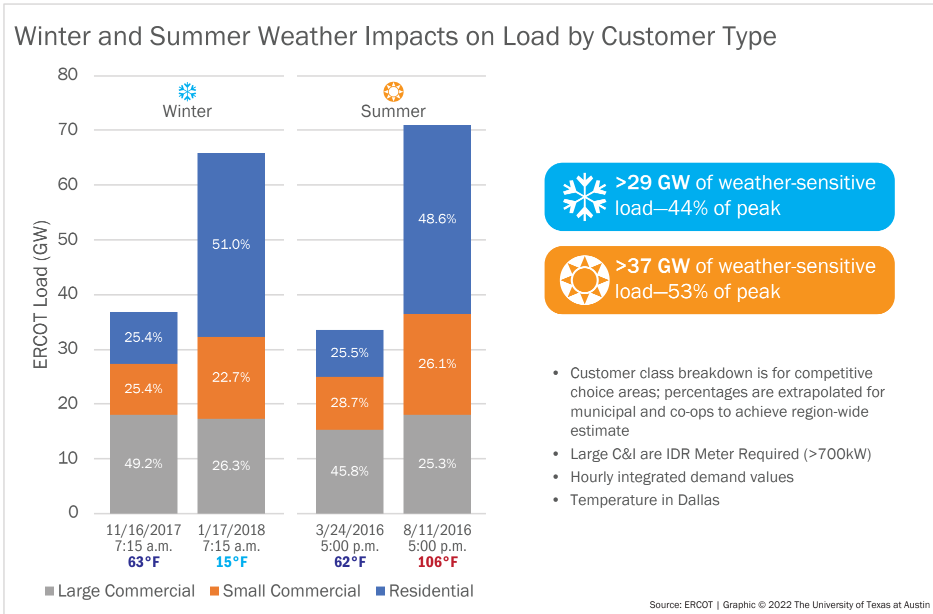

Figure 1: The residential sector in ERCOT (the Electric Reliability Council of Texas) is responsible for approximately half of peak demand in the winter and summer [11].

A potential test case for answering these questions is the Electric Reliability Council of Texas (ERCOT) regional power grid. The ERCOT grid is comprised of a generation mix with high fractions of wind and solar, which much of the U.S. system may soon resemble [12]. Additionally, a large portion of Texas is in a semi-arid temperate climate and has population centers in hotter and more humid parts of the state. Consequently, electrical heating equipment, which is typically designed for more moderate temperatures, is prevalent. The percentage of Texas household heating that is met by electricity is increasing over time and is the 7th highest among U.S. states [13]. Thus, the demand-side of ERCOT also resembles a future decarbonized grid.

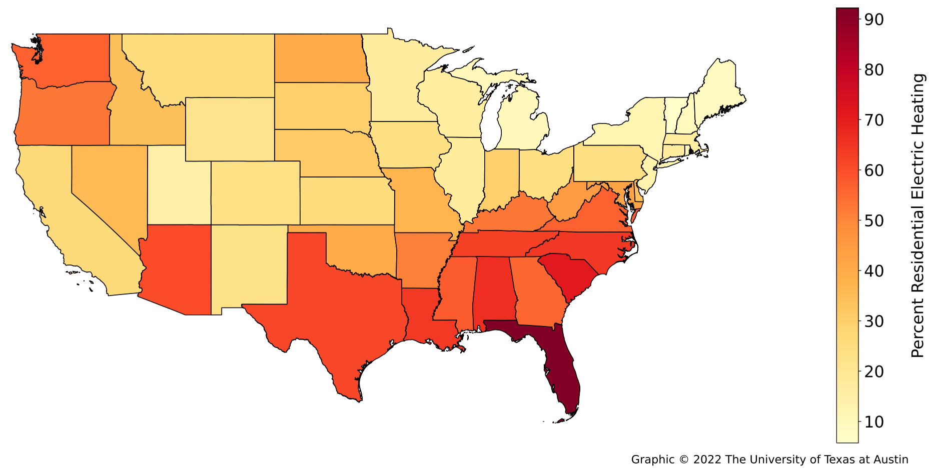

Figure 2: As of 2019, Texas had one of the highest rates of electric heating in the residential sector in the United States [13]. Generally speaking, electric heating is more prevalent in warmer climates (e.g. the southern part of the United States) or where there is abundant hydroelectric power (e.g. the Pacific Northwest).

As a result of the warm climate, ERCOT resource planners have prioritized managing the natural gas system and electricity grid such that they can meet the demand from large amounts of electrically-operated air-conditioners on hot summer afternoons. However, the events of the winter storm in February 2021, which caused hundreds of deaths and blackouts and boil water notices for millions of people, plus prior winter storms in 2011, 1989, and 1983, among others, should serve as reminders that Texas is not immune to extreme, widespread regional winter weather that strains infrastructure reliability [14–17]. These winter grid resiliency challenges could yield important lessons for future grid operators in increasingly electrified economies.

The winter event of February 2021 left millions of Texans in ERCOT without power for multiple days during some of the coldest and most widespread winter weather seen in the state in decades. In fact, February 2021 was the first time in recorded history that all 254 counties of Texas were under a winter storm watch at the same time. [18]. This event presents the opportunity for a unique case study on a highly electrified region subjected to severe winter weather.

Having lost roughly half of all power generation capacity due to freezing equipment, fuel shortages, and other issues, the grid was minutes away from conditions that could have triggered a total system-wide blackout that then could have required weeks or months for full recovery [16].

Given that Texas is the largest energy producing and consuming state in the United States [19], it was a surprise to have a widespread energy outage that caused hundreds of deaths. As such, there has been public outrage and demands for change to prevent a similar disaster. Almost every relevant government agency including the Governor's office, the State Legislature, Railroad Commission (which is the oil and gas regulator in Texas), the Public Utility Commission of Texas, and ERCOT have faced intense scrutiny or had its top leadership replaced. Because they are under pressure to implement new regulations or market reforms to prevent a future disaster, there is a need to inform the policymaking process in Texas and other regions that may face similar challenges with data about key underlying trends.

While many reports have assessed the underlying acute causes of the February event itself and its meteorological underpinnings [14, 16, 17, 20, 21], to the authors' knowledge, none have taken a look at how seasonal peak demand has changed over time nor investigated how non-flexible heating electrification may have contributed to the disaster. This analysis seeks to fill that knowledge gap.

2. Methods and discussion

The methodology for this analysis is simple in principle yet allows for some important observations. Peak demand data for the past 25 years in ERCOT were compiled for the winter (December through February) and summer (June through August) seasons [16, 22–25][1]. A linear regression was used to assess their growth over the 25-year period and the effect of ambient temperatures on

[1] 2001 summer peak demand sourced from [25] as "July Load at ERCOT Coincident Peak kW".

these events was investigated. Figure 3 shows how the winter[2] and summer[3] peaks have grown relative to each other along with a linear regression for each season.

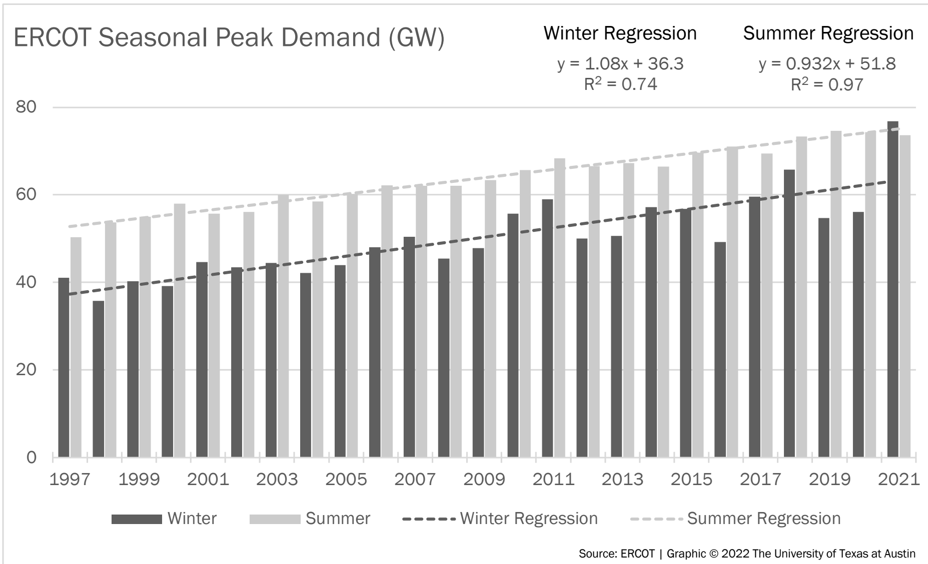

Figure 3: Winter and summer peak electrical demand in ERCOT grew from 1997 to 2021. The bars are actual (or estimated peak demands if load shed happened) peak demands and the dotted lines are the linear fit estimations of peak demand for each season and each year.

General observations of the results yield two main conclusions; 1) ERCOT's winter peak is growing about 15% faster than its summer peak, based on the slopes of the linear regressions and 2) the winter peak is more erratic than the summer peak, based on the lower R-squared values of the same regression. The winter peak is, on average, about 3.5 GW off (above or below the mean of

[2] Winter peaks in 2011 and 2021 were estimated because firm load shedding prevented the full load from being served. The peaks for those years were taken from ERCOT estimates of what load would have been absent load shed. Winter peak in 2001 was taken from an ERCOT report as 2001 load data were not available.

[3] Summer peak in 2001 was taken from ERCOT Coincident Peak Calculations as 2001 load data were not available.

the absolute values of the regression model errors) the linear model estimation, while the summer peak is only about 1 GW off, on average. Figure 4 shows how each year's summer and winter peaks differ from the linear model's prediction.

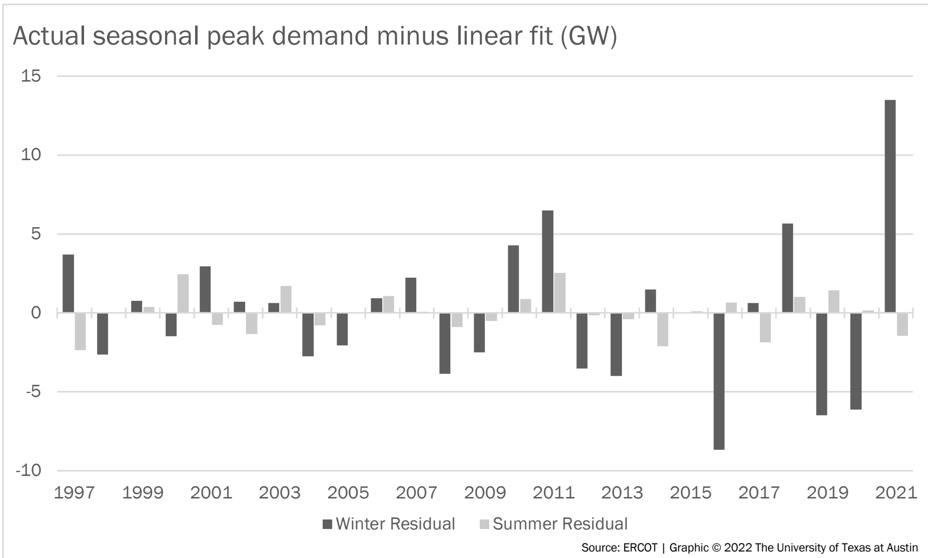

Figure 4: The difference between the estimated seasonal peak and the actual peak for each year shows that winter peak demand is much more variable (and therefore harder to predict) than summer peak demand.

The linear fit in Figure 3 shows that the summer peak demand growth is more "stable" (or consistent) than the winter peak. A visual inspection of the fit (dotted lines) versus the actual[4] peak demands (bars) shows that the summer peak growth is more linear than the winter model. This conclusion is also indicated by the R-squared values of the respective models (higher R-squared values correspond to higher linearity): R-squared value of 0.74 in the winter vs 0.97 in the summer.

The lower R-squared value of the winter model indicates that the growth in winter peak is less predictable. The summer peak is presumably a combi-

[4]Estimated peak demands in case of any firm load shed.

nation of consistent population and economic growth trends offset somewhat by efficiency improvements to space conditioning appliances. The winter peak has similar factors with two confounding weather factors from climate change: slowly increasing average prevailing temperatures (which reduces average total seasonal energy for heating) and ongoing risk for intense winter storms.

Since the general formation of ERCOT, the annual winter peak has never exceeded the summer peak. If the current rate of change shown in Figure 1 continues, it would take over 100 years from the start of the analysis (1997) for the average winter peak to systematically surpass the average summer peak. However, if the ERCOT grid had been able to deliver as much power as was estimated to have been demanded in the winter storm of February 2021 [16] the winter peak would have surpassed the summer peak for the first time since the Texas grid operator began recording data for its modern grid footprint. Furthermore, if electrified heating deployment rates accelerate, then the summer peak demand will grow less quickly (because of commensurate upgrades to air conditioning efficiency) and the winter peak demand will grow more quickly, in which case it is reasonable to anticipate that the winter peak will regularly exceed the summer peak much sooner than a century from 1997.

Because of the higher variability, peak demand projections for ERCOT, which are generally based on a "normal weather year" and are generally linear [26], should include more uncertainty on the forecasted winter peak than the summer peak.

While the summer cooling season ramps up and down over several months, the winter heating season is much more erratic. For homes with electric heating, the increase in demand for home heating when outside temperatures drop to levels seen in February 2021 is larger than the demand is for home cooling when a heat wave pushes temperatures to summer peak levels [27].

While the residential sector is generally responsible for most of the large swings in demand, residential demand response in ERCOT is small relative to commercial and industrial demand response [28]. As such, residential demand response programs that seek to reduce peak demand are mostly an untapped potential solution for grid reliability.

Weather influence on peak demand. Degree day data indicate that, over the past 25 years, temperatures were more erratic on winter peak demand days than on summer peak demand days. A degree day compares the mean outdoor temperature for a location to a base temperature as a measure of cooling or heating load [29]. Cooling degree days (CDD) and heating degree days (HDD) are calculated using ambient temperature readings collected at a particular location throughout the day. The time in days between two temperature readings is multiplied by the number of degrees by which the ambient temperature was above or below the base temperature over the period to get the degree days [30]. The further the ambient temperature is above or below the base temperature, the higher the CDD or HDD respectively, and thus the higher the cooling or heating load.

$$CDD = \sum time\ between\ temp\ readings\ (days) \times (ambient\ temp - base\ temp)$$

$$HDD = \sum time\ between\ temp\ readings\ (days) \times (base\ temp - ambient\ temp)$$

In this study, we calculated the number of degree days during each peak demand day. The base temperature for calculating both CDD and the HDD was set to 18.5° C (65.3° F) and an ERCOT-wide degree day (DD) value was calculated by taking DD values from the largest city in each ERCOT weather zone [31, 32] and weighting each DD value by the population in the weather zone[5] [33].

$$ERCOT\ DD = \sum DD\ from\ largest\ city\ in\ each\ weather\ zone \times \frac{weather\ zone\ population}{total\ ERCOT\ population}$$

[5]2021 population projected based on 2019-2020 percent population growth.

Figure 5: ERCOT uses eight weather zones for planning purposes [34].

CDD on summer peak demand days were fairly constant near the mean CDD value. However, HDD for winter peak demand days were more erratic and varied widely from the mean value (Figure 6). The unpredictable nature of the temperatures on winter peak demand days and more consistent temperatures on summer peak demand days is mirrored by the heating and cooling loads, respectively.

Weather Zone	City	Weather Station ID	Average Summer Peak Demand Day CDD	Average Winter Peak Demand Day HDD
Coast	Houston	KIAH	12.50	16.22
East	Tyler	KTYR	13.01	19.83
Far West	Midland	KMAF	11.88	20.93
North	Wichita Falls	KSPS	13.57	22.56
North Central	DFW	KDFW	14.81	20.44
South	Corpus Christi	KCRP	11.59	13.39
South Central	Austin	KAUS	12.63	17.57
West	Abilene	KABI	12.72	21.61

Table 1: Summary of weather stations used in calculation of state-wide population-weighted CDD and HDD values and average CDD and HDD values.

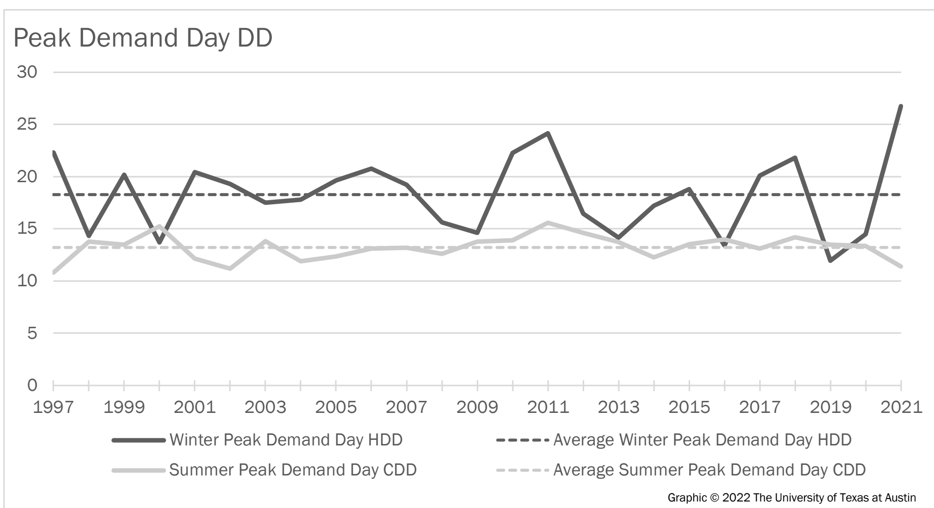

Figure 6: CDD and HDD values in ERCOT on peak summer demand days and peak winter demand days, respectively, show greater variability in winter peak demand for heating. ERCOT-wide DD values are calculated from DD values for the largest population center in each ERCOT weather zone weighted by the population of each weather zone.

These weather trends that drive heating and cooling loads impact power grid operations. Overall, about 55% of residential heating equipment in the West South Central census region of the US, which includes Texas, is electric. Of those electric heaters, about 85% are electric resistance and the remaining 15% are heat pumps [35]. Electrical resistance heating has very high power draws as compared to other forms of heating, such as heat pumps. Heat pumps can provide heating using much less electricity most of the time. However, many of the heat pumps installed in the region are not cold-weather heat pumps, rather they are usually designed for mild climates, and thus are only able to operate down to a specified low outdoor temperature before switching to backup or auxiliary heating modes that rely heavily on electric resistance heating or natural gas [36, 37]. When this switch happens, it can create a large jump in the electricity demand of each individual heating system that in aggregate can create a large upward disruption in grid demand as a cold front moves through. An analysis of per capita winter peak demand versus HDD exhibits this effect: per capita winter peak demand appears to have a polynomial relationship with degree days, becoming increasingly high for higher HDD (Figure 7). Additionally, data points from more recent years with higher penetration of electric heating tend to reside above the regression line, indicating that more electricity is consumed per capita when more electrical heating equipment is connected to the grid.

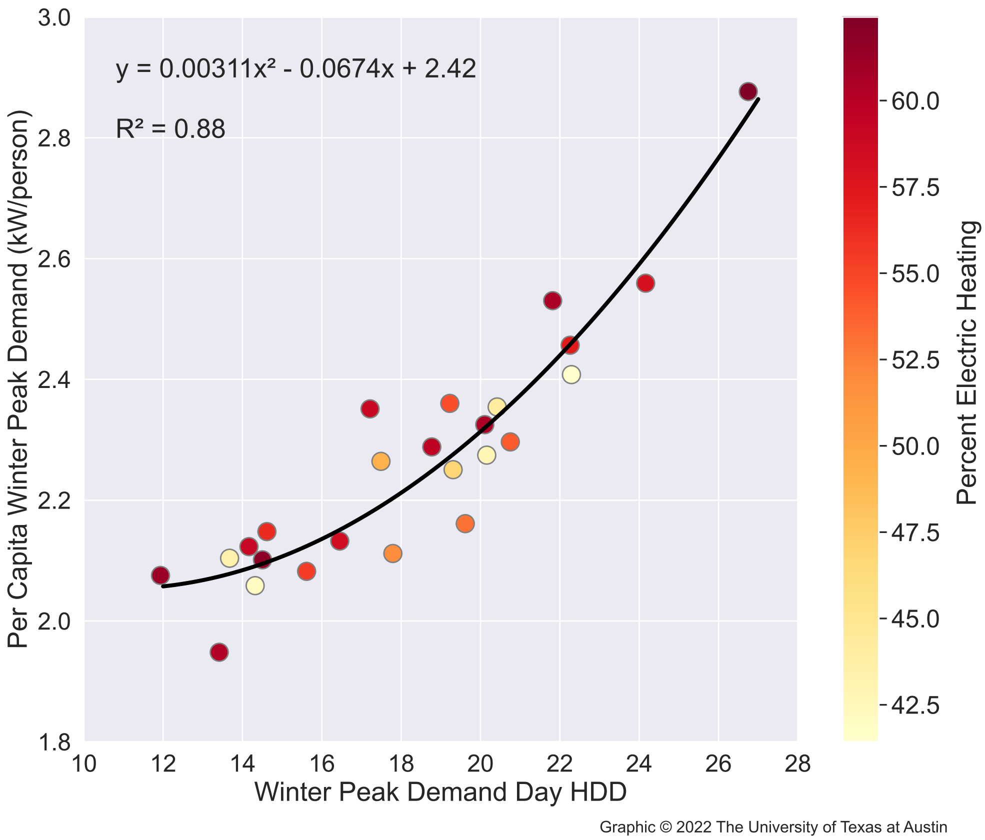

Figure 7: The relationship between 1997-2021 per capita winter peak demand and winter peak demand day HDD appears to be polynomial. Percent heating electrification data for this figure was sourced from the American Community Survey [13] and the Residential Energy Consumption Survey [35] and interpolated or extrapolated for years in which data was not available.

Normalizing the peak demand data by population and weather demonstrates that the summer per-capita, per cooling degree day peak demand is decreasing, indicating that the electrical efficiency of meeting the summer peak demand is increasing (Figure 8).

However, the winter per-capita, per heating degree day peak demand is increasing, indicating that the electrical efficiency of meeting the winter peak demand is decreasing. However, unlike the summer peak demand which has been driven by electrically-powered air-conditioners for the entire period of our dataset, the makeup of heating equipment has changed over time. For example, in 1997, only about 40% of homes in Texas used electrical heating, but that number has increased over time, meaning that the percentage of homes heating with other fuels, such as natural gas, has declined [13, 35]. Analyzing the flows of natural gas is beyond the scope of this analysis, but the positive slope, in Figure 8, of the winter per-capita, per heating degree day peak demand linear fit does indicate (although weakly) that electricity use in the winter is generally increasing even when population and weather are considered.

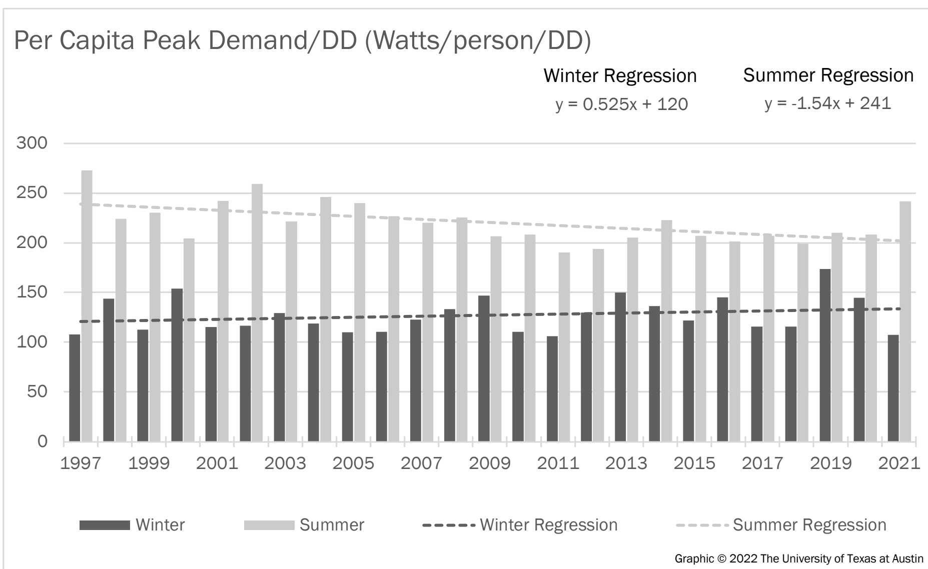

Figure 8: Per capita peak demand per DD is decreasing over time for summer peak demand days and increasing over time for winter peak demand days.

3. Suggestions for system and resource planning

As Texas and other regions electrify heating, more attention will need to be given to the impacts of extreme periods of cold weather on winter peak demand. Increased efficiency and cold-weather standards for heat pumps could allow the continued electrification of heating to avoid making as big of an impact on winter peak demand by delaying the individual heater's switch into auxiliary (electric resistance) mode, thereby reducing how often demand grows polynomially.

Increased residential building envelope efficiency could also reduce the amount of heating needed by the average home which would reduce the amount of individual coincident heating systems operating and thus lower overall heating demand from the residential sector. Most of Texas is located in "hot" climate zones and thus more attention has been paid to constructing homes to withstand high summer temperatures. Homes in Texas are generally designed to have adequate insulation levels and heating systems to withstand -4C (25F) [30] and are thus not prepared to cope with the much colder temperatures from events such as the winter storm in February 2021.

On the demand side, it's worth noting that because half of the peak demand in winter and summer is from space heating and cooling, these end-uses represent a significant opportunity for demand response (e.g. dispatching an intentional reduction in peak demand by turning off heating or cooling devices). These factors have led grid operators to posit that water heating and HVAC are good candidates for load control, and could allow buildings to provide grid services as thermal batteries [9]. If equipment with flexible features is installed, then rotating shut-offs to electric air conditioners and heaters can help preserve grid reliability and can be cheaper and quicker to install than to build additional generating supply.

On the grid supply side, it should be noted that by the end of 2022 it is possible that 4-5 GW of Texas power generation (or $\sim$5% of total Texas generation capacity) will come from the distribution grid [38]. These distributed energy resources (DERs) could provide valuable grid services if properly coordinated.

Price signals and/or incentives should be administered to ensure that DERs are optimally placed to provide grid reliability and cost benefits [38]. Additionally, increased attention to resource adequacy levels in the winter should be a focus for future operations. While beyond the scope of this work, it is possible that the addition of a new winter reliability product for the ERCOT market might be necessary to meet the additional challenges that are associated with the increased uncertainty in predicting the winter peak demand.

In general terms, grid planners can have reasonable confidence that each summer in ERCOT will be hot, but less certainty around how cold each winter will be. Thus, this finding would indicate the ERCOT grid might need more reserve capacity (higher reserve margin) to handle higher levels of uncertainty in peak demand in the wintertime than in the summer, particularly if the electrification of heating continues.

Currently, generation maintenance outages for generators and transmission assets are restricted between May 15 and September 15 so that most assets are ready to meet the summer peak demand. However more attention might need to be placed on having more capacity online during winter months to cover the higher levels of uncertainty. But squeezing more generation outages into smaller periods of time might then create supply shortages in the shoulder months.

4. Conclusions

This analysis assessed the relative change in summer vs. winter peaks in ERCOT from 1997 to 2021 and found that while the summer peak demand growth is relatively stable, the winter peak demand growth is less so. Additionally, it was shown that the instability of the winter peak demand growth is a consequence of erratic winter weather and electrical heating that becomes increasingly inefficient at lower temperatures. These results imply that special attention will need to be paid to how ERCOT and other grid operators plan for winter heating seasons, particularly given the trend of heating electrification in the residential sector, which was already the swing consumer of electricity in both the summer and winter seasons. Namely, planners should use higher uncertainty in their estimates for peak winter demand. Increased general efficiency standards for buildings and in particular heat pumps could mitigate some of the demand side winter issues and an increased level of uncertainty placed on the aggregate electricity grid winter peak demand estimates could help drive policies to increase winter reserves.

5. CRediT authorship contribution statement

Matthew J. Skiles: Data curation; Formal Analysis; Investigation; Methodology; Visualization; Writing – original draft, Writing – review editing. **Joshua D. Rhodes:** Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Visualization; Writing – original draft, Writing – review editing. **Michael E. Webber:** Supervision, Writing – review editing, Project administration.

6. Acknowledgements

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