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Quantifying the impact of residential space heating electrification on the Texas electric grid

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ABSTRACT

In this technical analysis, we studied the effects of complete electrification of space heating in the Texas residential sector on the energy consumption, peak power demand, and grid capacity utilization in the Electric Reliability Council of Texas (ERCOT) electricity grid. We utilized the National Renewable Energy Laboratory's (NREL) ResStock tool to develop geographically representative housing stock models and the physics-based EnergyPlus modeling software to create an aggregate building stock energy model that represents the residential sector in the ERCOT operating region. In this aggregate building energy model, we replace all natural gas and other fossil-fuel furnaces with reversible electric heat pumps of varying efficiencies that can provide heating in the winter and cooling in the summer. We integrate spatially-resolved actual meteorological weather data with the building stock energy model to simulate a specific year (2016) of hourly-resolved energy usage in the ERCOT region. We find the annual electricity consumption, peak hourly power demand for each day, and load duration curves for each of 17 regions within ERCOT. From the base case, the absolute winter peak electrical power demand in the residential sector could increase by as much as 36%, or 12 GW. These results indicate that grid capacity would need to increase by 10 GW (a 25% increase for the residential sector) to accommodate a winter peaking residential sector. Though winter electricity consumption would increase for home heating, the annual amount of electricity consumption would stay roughly the same or decrease because the higher efficiency heat pumps provide more efficient cooling than the conventional air conditioners they also replace. Using average 2018 emissions rates, we estimate a change to standard efficiency heat pumps would lead to a 4.1% reduction of CO_2 emissions and a 5.8% reduction of NO_x emissions from the residential sector. There is no significant change in SO_x emissions in our standard efficiency scenario, but in the high and ultra-high aggregate efficiency scenarios, SO_x emissions are reduced by 8.3% and 15.0% respectively.

1. Introduction

1.1. Motivation

The global push to decarbonize includes consideration of electrifying the residential sector [1]. A full electrification of the residential sector would involve replacing fossil-fuel powered appliances with those powered by electricity, including space heating systems. One of the most efficient and popular options to replace a fossil fuel-based furnace is an air-source heat pump (ASHP) [2]. During heating months, ASHPs use electricity to pump heat from the outside air to the inside of a household. During cooling months ASHPs reverse this process and remove heat from the household. ASHPs are a popular method of heating homes in several states in the southeast U.S., and are gaining popularity in cities with electrification policies—like the Californian cities of San Jose and Berkeley [3]. Both cities passed ordinances to ban natural gas in most new residential buildings beginning in 2020 [4,5]. With the possibility of similar ordinances being passed in other areas of the United States in the future, it is important to understand the impact of electrifying space heating on total and peak electricity use.

As of 2015, 34% of U.S. households used electricity as their main fuel for space heating [6], thus a large potential for electrification exists. Prior literature indicates that a high penetration of electrified residential space heating has the potential to significantly shift total electric grid load shapes and change the season in which some grids' annual peak demand occurs [7,8]. Significant changes in load shape could especially affect Texas, where the Electricity Reliability Council of Texas (ERCOT) operates the Texas Interconnection—an "islanded"

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electric grid with a small number of low-grade connections with the two other mainland grid systems in the United States.

In 2018, the Texas residential sector consumed 37% of total electricity generation in the state and contributes disproportionately to system peak load (53% in 2011) [9,10]. The Texas Interconnection is a summer-peaking electric grid, primarily driven by most Texas residences using their air conditioners. Only 1.1% of Texas households report not having air conditioning equipment [11]. During summer peak hours, residential sector loads make up approximately 50% of the ERCOT load, compared to 25% for the small commercial sector, and 25% for the large commercial and industrial sector [12]. For reference, ERCOT peak demand for the year 2018 occurred on July 19 between 4 and 5 p.m. at a value of 73,308 MW while the winter peak that year occurred on January 17 at a value of 65,915 MW between 7 and 8 am [13,14].

During winter peak hours, residential sector load makes up approximately 51% of the ERCOT load, small commercial load makes up 23% and large commercial and industrial makes up 26% [12]. Approximately 60% of households use electricity as their primary heating fuel [15]. The most recent applicable residential survey estimates around 5% of electric-heated Texas households utilize electric heat pumps and the remaining 95% of households use electric heating via electric resistance furnaces, baseboard heaters, or plug-in heaters [11]. Texas's percentage of electric heating is higher than the US average and is likely the result of a relatively small heating demand in Texas' comparatively warmer climate. However, this warmer climate is still susceptible to extreme cold snaps due to strong polar cold fronts in the winter. In February 2021, the Texas grid encountered unparalleled residential demands as sub-freezing temperatures persisted over the state for consecutive days, causing statewide load shedding that resulted in millions of households without power for multiple days.

During extreme weather events, residential loads drive the system's peak demand. Replacing the heating units of the remaining 40% of fossil fuel heated households with reversible electric heat pumps can have significant effects to both the summer peak load and the winter peak load. Quantifying time-resolved electricity usage of a residential sector with 100% electric space heating provides helpful information for electric grid operators and grid capacity planners as they consider electrification programs.

1.2. Background

1.2.1. Literature review

A variety of energy simulation software packages are available to quantify a specific building's energy usage and performance. These programs often calculate energy usage through dynamic modeling of conduction, convection, and radiation within the structure [16]. Two commonly used dynamic modeling software programs are TRNSYS and EnergyPlus [17,18]. EnergyPlus, developed by the U.S. Department of Energy, allows users to modify household attributes and collect energy consumption data of specific end uses within the structure. Unlike computationally-lean static models, EnergyPlus requires a moderate amount of computing power. It can take on the order of a few minutes to process hourly usage information over one year for a 100 square meter home using a modern personal computer. This computational cost puts practical limitations on some applications like modeling the usage of a large group of homes that represent a neighborhood or city. However, this approach, known as Urban Building Energy Modeling (UBEM), is necessary as it aids policy makers in decisions regarding the intersection of residential sector building stock efficiency and residential sector energy consumption [19]. To reduce the computing resources needed to model large groups of buildings, researchers often model a relatively small number of archetypes that reflect the total unique types of units that occur in a specific region. Some studies also further lower the computing demand by decreasing the complexity of the dynamic thermal model. This simplification is achieved by reducing the system to discrete thermal resistances and capacitances (RC), i.e., lumped-capacitance models.

These methods are often used in research on residential electrification. Many studies conclude that residential heat pump adoption is an integral part of decarbonization through electrification and thus the reduced use of carbon-emitting fuels in the home [3,20–25]. Cooper et al. [26] uses a lumped-capacitance model paired with archetyping to find the peak net-demand in the UK if there was widespread heat pump usage. Reyna & Chester [27] uses EnergyPlus with a method of archetyping households in Los Angeles county (USA) to forecast electricity usage and explore the potential for energy efficiency (including heat pump efficiency) to offset increased demand. This method is also used in Burillo et al.'s [28] work about the effects of increasing air temperature in Los Angeles County on peak electricity demand. Many other studies focus on modeling residential heat pumps as part of strategies to shift loads from peak hours to off-peak hours through thermal energy storage (TES) materials and demand response (DR). This body of research commonly uses optimization algorithms that benefit from a simpler model than the dynamic models seen in EnergyPlus or TRNSYS, and thus many use a lumped-capacitance RC dynamic model.

The archetype method of modeling many buildings' energy usage has proven useful for modeling urban and regional building stocks [29]. This method develops an array of typical household models from a particular region's residential building stock data. The models' energy usage is then scaled according to the actual number of households in the specific region. These models help identify potential for cost and energy savings within a locale's building stock [30]. However, the archetype method for UBEM has its limitations. Chen et al. [31] and Reinhart & Davila [19] note that the UBEM workflow is not generalized. This characteristic of UBEM is because of the lack of standardized building stock data across regions. The lack of standardization makes it challenging to describe building archetypes such that they reliably represent a region's housing stock.

An additional limitation is the tradeoff between number of archetypes in the energy model, geographic resolution, and available data. Reyna & Chester [27] created 51 archetypes to reflect the Los Angeles county building stock and use EnergyPlus to simulate 83,640 simulations with those archetypes over 41 years and 40 climate forecasting scenarios. Cooper et al. [26] use the lumped-capacitance model to simulate 5 building archetypes over 960 different dwelling permutations across the UK. The UK study covers a large region with the lumped-capacitance models calibrated to more detailed simulations. The Los Angeles county study is enriched by publicly available information about the county's building stock, the county's appliance usage, and the state's assessor handbook. Focused data allows the study to dive deep in a small geographic region but covering a diverse span of regions following the same method would be cumbersome.

The building stock simulation studies mentioned above are general and do not specifically focus on electrification of heating via replacement heat pump system installations. Much of the literature related to understanding the impact of heating electrification with heat pumps on electric grids focuses on peak shifting from the building's perspective. Most DR studies optimize heat pumps paired with TES materials in a single or fleet of houses, coupled with pricing signals, to minimize energy or economic costs. There are many tradeoffs upon choosing a method to obtain energy demand for buildings. Baeten et al. [32] use a lumped capacitance RC method to model a household. However, simple lumped capacitance models have been found to underestimate peak loads by more than 10% [33]. Some studies use EnergyPlus or TRNSYS to model small numbers of households, but do not study demand from large groups of homes [34,35]. Other TES optimization studies use actual measured data from metering trials or sharing agreements [21,36,37]. Measured data, however, are generally difficult to acquire or find in the literature [38]. Although there are multiple methods for TES optimization studies to obtain energy demand data for a household, it is either hard to obtain or outside the scope of the study to spend resources on sophisticated demand modeling.

Some studies project the large-scale grid impacts of heating electrification via heat pump adoption. Love et al. [39] uses a relatively large heat pump trial dataset to project future electricity use from electrification. The heat pump trial data was adjusted for diverse occupancy behavior and scaled up to as large as a 20% heat pump adoption rate in the UK. Love et al.'s [39] utilization of heat pump trial data to project future demand contributes a novel estimate of the UK electric grid's future peak demand and ramp rate. Eggiman et al. [40] studies the DR potential of a high uptake of heat pumps in the UK through a bottom-up modular demand simulation model dependent on scenario data and socio-technical drivers such as technology improvements, population changes, and occupancy behavior changes. Although it is not central to the demand simulation model, a building stock model is used as a scenario driver to identify how changes in dwelling characteristics affect demand. Eggiman et al.'s [40] modular demand simulation model produces a spatially and temporally resolved energy demand projection for a 50% heat pump penetration electrification scenario. Boßmann & Staffell [41] project future electricity demand in the UK and Germany by scaling load curves according to applications seen to be relevant in the future. Although it is not an ostensible electrification study, heat pump adoption rates are used for the study's 2050 projection—21.6% (UK) and 7.8% (Germany).

These three studies simulate the demand from households, but they do not rely on physics-based building energy modeling (such as UBEM). Rather, they use existing datasets and/or future technical projections to model future electrification demand scenarios. Love et al. [39] and Eggiman et al. [40] model the demand from heat pump adoption in a location that sees cool winters, rather than a climate with colder winters that could push heat pump performance to its limits. Boßmann & Staffell [41] model heat pump uptake in the colder climate of Germany, but the adoption rate in the study is less than 10%. While the contributions of the three studies are valuable for the future of electric grid operations and planning for mass residential electrification, the lack of physics-based modeling and lack of variation in extreme cold weather and heat pump penetration rate is seen as a limitation.

1.2.2. Research gap identification

Modeling residential demand with hourly or sub-hourly resolution is required to understand how changes to the building stock (e.g., electrifying space heating in all households) will affect the electric grid. This high temporal resolution enables peak and load shape analysis as well as dispatch analysis if paired with a model of the supply-side of the electric grid. Thus, it is essential to have an accurate transient model of energy usage with a temporal resolution of at least one hour. Vivian et al. [33] finds that simpler, lumped capacitance models struggle in accuracy of transient energy usage compared to dynamic models. The methods for creating an accurate transient model are largely non-generalized due to variance in data, modeling engines, and spatial coverage. Complex dynamic models, such as Reyna & Chester's [27] forecast of residential demand in Los Angeles county, typically only cover a small geographic region. This variation in data leads to DR-optimization studies that must either acquire measured data from large groups of homes which can be difficult/expensive or implement optimization algorithms on simplified models with a small number of households. Large-scale grid impact studies of heat pump adoption rely on non-physics-based modeling techniques and lack geographic and climate diversity. Using more complex and dynamic physics-based modeling platforms cost computing resources and typically require multiple sources of data for inputs into the model. These tradeoffs typically lead researchers to pick one or the other. Thus, there is a knowledge gap in the literature that this analysis seeks to fill.

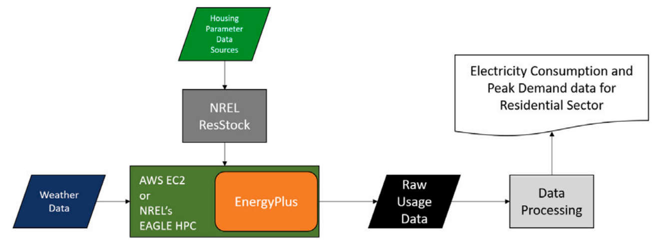

Fig. 1. Methodology flowchart for quantifying energy usage after full electrification of space heating in the ERCOT residential sector. To quantify residential electric load, the building simulation software, EnergyPlus, simulates thousands of households that are representative of the building stock within the ERCOT residential sector. NREL's ResStock analysis tool is used to generate the group of households from a statistically representative housing parameter space sample. The building simulation data is processed into electricity consumption and peak demand data for the residential sector.

1.3. Research question

Using physics-based modeling and existing building stock datasets, this paper answers the question of how the energy usage of a large, diverse residential sector would change if all space heating were electrified. Electrification of the residential sector changes energy use patterns and affects both the electric grid's annual energy consumption and seasonal peak demand. The remainder of this paper is structured as follows: Section 2 gives the methodology to quantify energy usage of an electrified residential sector, Section 3 presents the results of this study, focusing on peak demand, energy consumption, and emissions impacts and Section 4 formulates conclusions from the study.

2. Methodology

2.1. Model methodology

Overview

To model the impacts of the electrification of space heating on the Texas residential sector, this analysis utilizes the National Renewable Energy Laboratory's (NREL) ResStock™ analysis tool and synchronous historical weather data from locations around Texas. Fig. 1 gives a graphical representation of the entire workflow. The ResStock analysis tool samples location-specific housing parameters to construct thousands of representative households and then simulates them using the EnergyPlus engine [42]. ResStock is classified as a Q4 physics-simulation type of generating statistically representative households [43].

2.1.1. Aggregate building energy model

EnergyPlus is a dynamic building energy modeling software that simulates a building's thermal envelope and models its energy usage according to thermal equations [17]. This software simulates the energy usage for every household in this study. The software requires many discrete inputs to describe a household (e.g., 3D coordinates of all surfaces, insulation type, HVAC parameters, glazing information). This high number of inputs has been listed as a limitation on its usage as an modeling software [33].

This paper's methodology uses the ResStock analysis tool to overcome this limitation. The ResStock analysis tool automatically generates a group of households from a statistically representative housing parameter space sample [44,45]. The parameter space uses housing stock data from more than 11 different sources to determine probability distributions for each residential housing parameter as a function of location [42]. For this study, ResStock was used to create approximately 38,000 households to represent the 8.8 million homes across the ERCOT operating region, a ratio of around 230 real homes for each model. Fig. 8 in the results highlights the variability between the study's homes

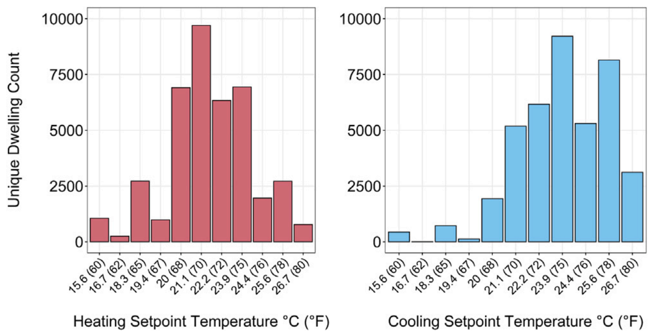

Fig. 2. Heating and cooling setpoint temperatures for all household simulations used in this study. Temperature setpoints determine a household's target temperature for its conditioned space during a respective heating or cooling hour. Temperature setpoints have a significant effect on the heating/cooling load scheduling for a household.

via violin and box plots describing the annual energy consumption of all households. These households include single-family attached, single-family detached, and multi-family low-rise homes. At the time of the analysis, multi-family high-rise households were not included in the ResStock analysis tool. Because each of the simulated homes are independent from each other, they can be modeled in parallel, which can significantly reduce computing time as each individual simulation can take up to 5 min on a single thread of a standard computer.

Diversified residential heating and cooling behavior is simulated through sampling probability distributions of cooling and heating setpoints, setpoint offsets, and setpoint offset periods that are dependent on 2004 ASHRAE IECC Climate Zone designations and building type (e.g. mobile home, single-family detached, multi-family low-rise, and so on). Cooling and heating setpoint diversity for this study's household set is shown in Fig. 2. Other consumer diversity factors like dishwasher use, clothes washer and dryer use, and number of occupants are determined by a similar method. Housing stock details for the 38,000+ households and information on probability distributions can be found on the public data repository associated with this study [46].

Because residential space conditioning demands are largely driven by weather patterns, it is important for studies that span large regions, like this one, to use as much temporally-matched data as possible. To simulate a historical weather environment, our study utilizes actual meteorological year (AMY) weather data from 2016 across 17 locations in Texas. The year 2016 was chosen because it involved a relatively hot summer corresponding to an ERCOT peak demand of 71 GW and a particularly cold stretch of weather in February. ResStock uses the U.S. Census American Community Survey and other geospatial data sources to estimate how many households correspond with each weather file location [45].

The individual simulations are typically executed on a high performance computer (HPC) or cloud computing system—this study used NREL's Eagle HPC [47]. The raw output data from each simulation are then processed and analyzed. The analysis process shown in Fig. 1 was repeated four times to include different heat pump technologies that reflect increasing cooling efficiency, using seasonal energy efficiency ratio (SEER), and heating efficiency, using heating seasonal performance factor (HSPF), as shown in Table 1. Higher SEER or HSPF ratings reflects a more efficient heat pump—one that uses less energy as to cool or heat the same cooling or heating load. Note that all existing electric heating efficiency levels (primarily electric resistance heating) were left as is. As a simplification, fuel-fired heating systems serving multiple dwelling units in multifamily buildings were assumed to be replaced with individual heat pump units serving individual dwelling units.

The raw output data from EnergyPlus contains energy usage for each of the 38,000+ housing units from each of the 8784 h represented in the 2016 historical weather files. This hourly energy usage data

Table 1
Scenario definitions. The standard efficiency air-source heat pump is rated at the federal minimum efficiency for the southern U.S. The high efficiency heat pump is a currently available high-end variable speed air-source heat pump. The ultra-high efficiency mini-split heat pump is currently available and represents the efficiency bound of currently available electric space heating technologies.

Scenario name	% Residential electric heating	Heat pump type	Cooling Eff. (SEER)	Heating Eff. (HSPF)
Base	57%	–	–	–
Standard Eff.	100%	Single-speed	15.0	8.5
High Eff.	100%	Variable-speed	22.0	10.0
Ultra-High Eff.	100%	Variable-speed	29.3	14.0

collected from each EnergyPlus simulation is multiplied by the 230 households each model represents. Energy use for each simulation is then summed and grouped by time and location. The resultant dataset displays the total electricity, natural gas, and propane consumption of every hour of 2016 for the ERCOT residential sector. The maximum hour of electricity consumption (kWh) for each day is divided by the change in time (one hour) to create an absolute peak hourly demand value (kW) for the day. These values for maximum hourly demand on each day are referred to in this paper as *daily peak demand values*. These 366 daily peak demand values are used to create a daily peak demand curve for ERCOT. Consumption and peak demand data from the base simulation are compared to the different heat pump technology scenario data to analyze annual consumption, net emissions, and capacity utilization. The hourly energy usage and daily peak demand datasets can be found at public data repository associated with this study [46].

2.1.2. Heat pump and auxiliary heating performance

Heat pump performance decreases as the ambient temperature falls below freezing. Auxiliary heating is sometimes necessary to supplement the heat pump and continue to meet the heating load of the conditioned space. In the southern U.S., this auxiliary heating source is usually electric resistance (also called "electric strip heat") heating which is less efficient than using the heat pump compressor [48]. All auxiliary heating required by the heat pumps in this study is met by electric resistance heat.

The degree of heat pump performance degradation depends on the specific model heat pump. The outdoor temperature below which auxiliary heating is needed can vary from 0 to −25 °C, depending on the specific model's performance and how it is sized relative to a location's design conditions [49]. The ASHPs modeled for this study were sized via an algorithm that is consistent with industry standards (e.g., ACCA Manuals J and S), which primarily selects heat pump capacities based on a home's design cooling load, but allows heat pumps to be oversized (15%, 20%, and 30% for single-, two-, and variable-speed systems, respectively) to meet a higher portion of the heating load in relevant climates. In colder climates, it may or may not be beneficial to deviate from industry standards and allow selection of heat pumps that can meet the entire design heating load without an auxiliary heat source. However, this decision was determined to not be relevant for this ERCOT analysis, where design cooling loads generally exceed design heating loads.

Fig. 3 displays the coefficient of performance (COP) of each of the three heat pumps used in the electrification scenarios of this study for every heating hour of a building energy model of a sample home in the Dallas, TX area using historical 2016 weather. The COP for an HVAC unit is the ratio of the heating load delivered to the conditioned space against the electricity consumed by the heat pump and HVAC heating fans to meet that heating load. The COP of the auxiliary electric resistance heating required during very cold hours is shown by the yellow triangles.

Heat pump system performance can be very sensitive to how the auxiliary heat is controlled. In a worst-case scenario, the heat pump compressor is locked out and no longer allowed to provide heat below

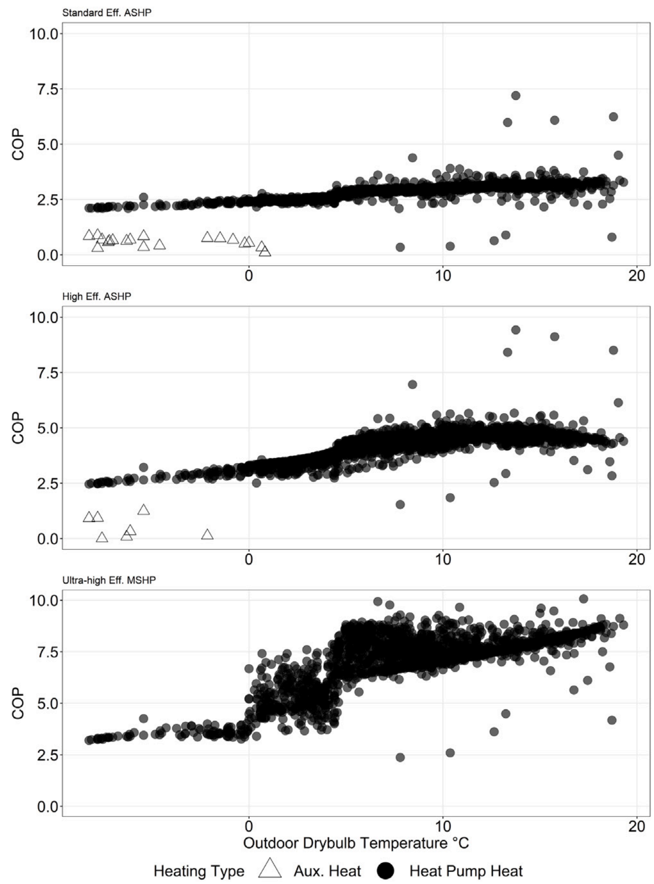

Fig. 3. Hourly coefficient of performance (COP) vs. outdoor dry bulb temperature for each of the three heat pumps used in the study's electrification scenarios, as simulated for 8760 h in a sample home in Dallas, TX. COP is the ratio between heating load delivered and the electricity consumed by the heating unit and the air handler fan to meet that heating load. Note that the ultra-high efficiency MSHP fully meets the heating load without using auxiliary electric resistance heat. COP is primarily a function of outdoor dry bulb temperature, indoor dry bulb temperature, and compressor speed; the spread in COP values for a given outdoor temperature is due to variability in compressor speed needed to meet the load in a given hour (does not apply to the single-speed Standard Eff. ASHP), variability in indoor temperature, as well as efficiency losses due to compressor cycling. The step-changes in COP are due to defrost mode operation (below 5 °C; function of outdoor wet bulb temperature) and MSHP pan heater (below 0 °C).

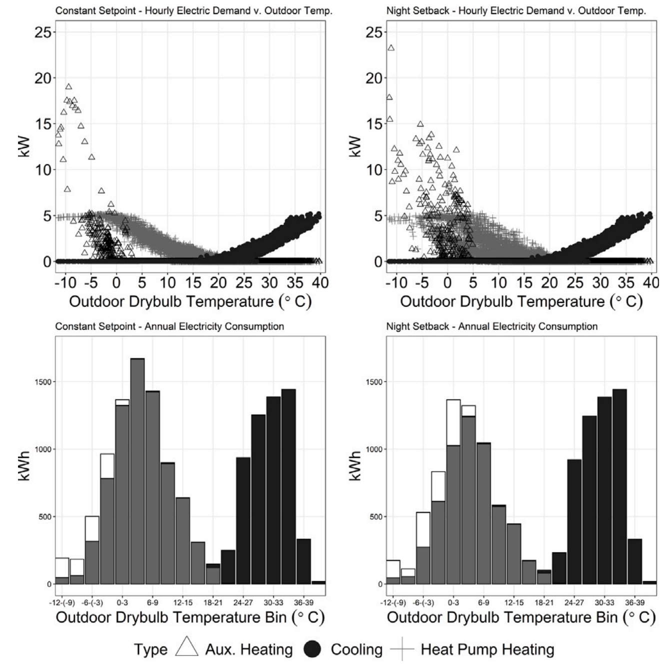

Fig. 4. Heat pump and auxiliary heat behavior are shown for an example older home in Dallas, TX with a SEER 15, HSPF 8.5 heat pump (consistent with our Standard Efficiency scenario). This figure illustrates that auxiliary heat control is an important factor in evaluating the impact of electrification on the grid. Additionally, the "night setback" case illustrates that reducing the heating temperature setpoint at night can increase overall usage of auxiliary electric resistance heat if auxiliary heat lockout control is not used.

temperatures around 0 °C. ASHPs that are properly installed will continue to provide some heat below 0 °C, with some specific models continuing to provide heat down to −25 °C. The ASHPs in this study's EnergyPlus simulations have their compressor lockout temperature set to −17.8 °C, which is below the *99.6% heating design temperature* found in the coldest parts of Texas (e.g., −12.2 °C in Amarillo, TX) [50]. The 99.6% heating design temperature represents the temperature that is lower than the outdoor temperature 99.6% of the hours in a year (in other words, the 0.4th percentile), based on 30-years of historical weather. The 99.6% heating design temperature (or the less conservative 99% version) are commonly used for heating load calculation for equipment sizing. Fig. 4 shows heat pump and auxiliary heat behavior for an example *older* home in Dallas, TX with a SEER 15, HSPF 8.5 heat pump (consistent with our Standard Efficiency scenario). While the heat pump continues to operate down to −12 °C, auxiliary heat is needed for about 200 h, primarily when outdoor temperatures are below 2 °C.

Auxiliary heat can also be deployed at higher temperatures when the thermostat is increased (manually or scheduled) and the heat pump cannot reach the new setpoint quickly enough [51]. Best practice installation (required by some state energy codes) involves locking out auxiliary heat above a certain outdoor temperature (typically around 2 °C to 4 °C) [52]. About half of the households in this study are modeled with a reduced heating setpoint at night (based on data from RECS 2009 [11]). Auxiliary heat lockout control was not modeled for this study; however, it is not likely to be relevant to the main conclusions of this study, which focus on the top hours of winter peak demand, since these hours occur below 2 °C to 4 °C in most parts of ERCOT (e.g., as shown in Fig. 4). If auxiliary heat lockout were implemented, it would reduce annual electricity consumption in the electrification scenarios (primarily the Standard and to a lesser extent the High scenario), however, it would not likely affect peak demand results.

2.2. Methodology limitations

There are a few limitations associated with this method. The households sampled by ResStock and modeled in EnergyPlus have not been fully validated against metered data because hourly 2016 residential load data is not publicly available. Results for annual energy use of single-family detached homes were validated in [41]; validation of timeseries results, including multifamily buildings is the subject of ongoing work [53]. Additionally, the sizing of heat pumps in this model is automated via an algorithm that is consistent with industry standards (e.g., ACCA Manuals J and S). However, it is well understood that the majority of residential HVAC systems are installed without performing detailed load calculations, commonly leading to system oversizing or undersizing [54]. Improper sizing could impact aggregate building load, but recent studies have found the impact of sizing on air conditioner load to be smaller than previously thought [54,55]. Because oversizing a heat pump by 20% has a bigger financial impact than oversizing a traditional gas furnace by 20%, installers of heat pumps may be more likely to perform detailed load calculations, which could moderate sizing impacts.

Another limitation is related to nightly temperature set point behavior. In our study, approximately 53% of the households with a heat pump use a constant temperature setpoint at night (i.e. the conditioned space's setpoint remains the same at night as in the daytime) and the remaining 47% use a setback temperature during the night time (based on data from RECS 2009 [11]). Having a night setback will result in higher heating demand in the morning when occupants wake up and become active. Our analysis assumed that all night setbacks end at 8:00 am, whereas in reality this timing varies by a few hours. This likely causes our model to overpredict winter peak to some degree. Fig. 4 shows how night setback increases peak hour demand by about 20% for an example household in Dallas, TX with a standard efficiency ASHP. If we modeled diversity in the timing of night setback recovery, this increase in peak would be diversified across several hours. Addressing setback timing diversity in future studies is a priority as it will more accurately reflect occupant behavior.

Finally, our study is limited in that it narrowly focused on residential space heating electrification. Although electrified water heating load is likely to change annual residential sector electrical loads in a significant way, it is outside the scope of this study [56,57]. Alternative pathways to decarbonization like renewable hydrogen are not explored in this study. Other parallel trends, such as population shifts, building stock turnover, increased cooling due to climate change, and electrification of other sectors (transportation, commercial, industrial, and other residential end uses) would also have an impact on power sector electricity demand, although residential space heating will continue to be the primary driver of winter peak demand. Our hourly consumption data will be publicly available for future studies that want to analyze it in combination with these other trends [46]. Despite these limitations, we believe this methodology is a sufficient starting point for modeling the residential electrification of a large, diverse geographic region covering a synchronous electric grid.

3. Results and discussion

Peak demand and consumption impacts

Quantifying the energy usage of the ERCOT residential sector with 100% electrified space heating shows how residential electricity demand trends could change by consumer-driven or policy-driven electrification. To show how electricity demand changes, we show a comparison of the daily peak demand for each day of 2016, between the current and a fully electrified residential sector, along with comparisons of load duration curves. Our results show that the electrification of space heating in the ERCOT residential sector causes the residential sector's demand to switch from a summer to a winter-peaking grid, with peak winter demand increasing by nearly 12 GW (see Figs. 5 and 6). Further, total electrification of heating requires an increased grid capacity to meet the new peak demand. Because the heat pumps provide more efficient cooling than the air conditioners they replace, annual electricity consumption either stays the same or decreases (when more efficient heat pumps are modeled). Lastly, emissions decrease in all electrification scenarios. We elaborate on these findings in the following subsections.

3.1. *Peak demand findings*

Our analysis finds that the timing of peak demand for the year for the ERCOT residential sector changes from the summer (driven by air-conditioning loads) to the winter (driven by heating loads) for every scenario we analyzed. From the base case, winter peak demand in the residential sector could increase by as much as 12 GW, a 36% increase. This change would likely require a shift in electric grid operations because the ERCOT grid has evolved its maintenance schedules to handle its largest loads in either late July or early August. Planned plant outages are typically scheduled in the shoulder and winter seasons because of lower load [58]. Grid investments are often driven by summer heat derating limits of transmission lines and power plants—something that might not be as big a factor for a winter peaking system.

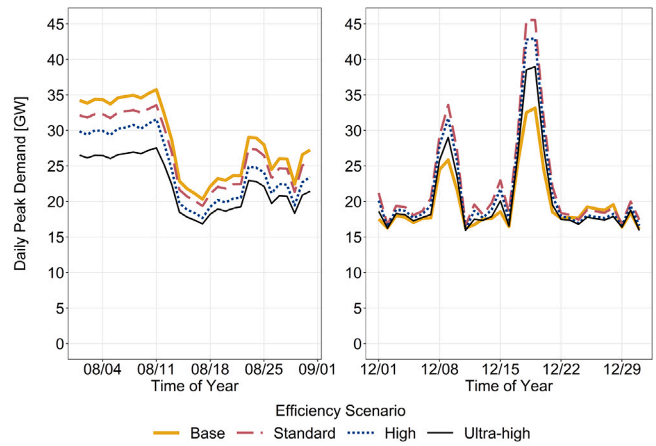

Fig. 5. Simulated residential sector daily peak demand (maximum hourly demand on each day) for the months of 2016 containing the summer and winter peaks : August and December. Daily peak demand data is shown for the current state of the ERCOT residential sector "base" (yellow thick line) and an electrified ERCOT residential sector with standard-efficiency ASHPs "standard" (pink long-dashed line), high efficiency ASHPs "high" (blue dotted line), and ultra-high efficiency MSHPs "ultra-high" (dark gray thin line). During the majority of December, the electrification scenarios' daily peak demand is higher than the base scenario.

Additionally, we find that the change in magnitude of peak hour between the current residential sector and an electrified sector varies by location. The further north and west in the ERCOT service area, the larger change in peak demand the county will see during its peak hour of the year.

3.1.1. *System-scale effects*

Figs. 5 and 6 show the daily peak demand for the base scenario (the current mix of residential heating types) and each respective electrification scenario. For example, Fig. 6's graph with the triangle and square datapoints reflects the high-efficiency scenario which involves replacing all residential fossil-fuel powered heating units with a variable speed SEER 22, HSPF 10 electrically-driven air-source heat pump. Each data point on Fig. 6 is the peak hour of averaged power demand for each day of the year in 2016 for each scenario. Fig. 5 shows the same data but only for the peak summer month and peak winter month. Both figures show the highest amount of demand from the residential sector that the electric grid will be required to meet for each day out of the year. Fig. 5's focus on August and December allows for a closer view of the summer and winter peak demand values and seasonal trends.

The base scenario's data show the typical demand trends from the ERCOT residential sector: (1) a system peak in late July or early August driven by high air-conditioning demand, (2) lower demand during late fall and early spring, and (3) local maxima during the winter when demand spikes because of cold weather. The electrification scenario shows how electrification changes the base case's trends: (1) the system peak occurs during the winter in December at 45 GW (25% higher than the base summer peak) for the standard efficiency scenario and (2) peak demands during the summer months are 6% to 22% lower, because the modeled heat pumps provide more efficient cooling than the air conditioners they replace. The reduction in the summer peak load could help mitigate increases in median summer outdoor temperature due to climate change.

The scenarios show that heating electrification in the residential sector is likely to push the ERCOT residential sector from a summer-peaking sector to a winter-peaking sector. Additionally, the scenarios indicate that lower summer peaks allow households with newly

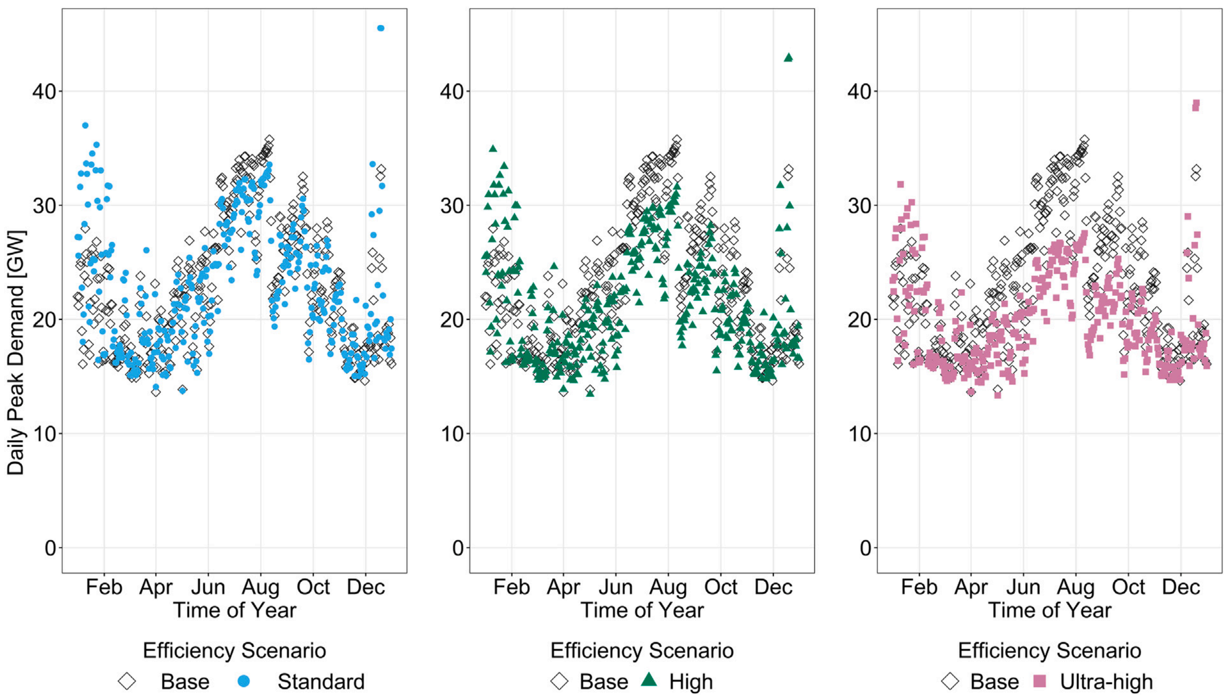

Fig. 6. Simulated residential sector daily peak demand (maximum hourly demand on each of the 366 days) using 2016 weather data for the current state of the ERCOT residential sector "base" (diamond) and an electrified ERCOT residential sector with standard-efficiency ASHPs "standard" (circle), high efficiency ASHPs "high" (triangle), and ultra-high efficiency MSHPs "ultra-high" (square). The electrification scenarios (circle, triangle, and square) show a residential sector that peaks in the winter. The summer daily peak demand is slightly less than the base scenario in the standard efficiency scenario, but daily peak demand significantly decreases in the high and ultra-high efficiency scenarios. This significant decrease is because the heat pumps provide more efficient summer cooling than the air conditioners they replace.

installed ASHPs to take advantage of their higher efficiency during cooling months, reducing summer demand.

These findings show how demands on the electric grid could change if residential heating were fully electrified. Peaker plants – power plants that are only utilized when there is high demand – would likely need to be dispatched more often in the winter. This change would likely have numerous impacts, such as changing wholesale electricity prices, impacting grid emissions profiles, and altering power plant maintenance scheduling. It could also affect the planning reserve margin (PRM) for ERCOT. The PRM is the percentage of projected capacity above the projected peak demand [59]. The North American Electric Reliability Corporation (NERC) highlights ERCOT as having potential reliability issues because of its slim PRM [60]. The targeted PRM for ERCOT is 13.7%, but was 10.6% in 2018 [61,62]. Since the residential sector's winter peak of the Standard efficiency electrification scenario is more than 10% larger than the residential sector's summer peak of the base scenario, a fully electrified residential sector could drive large-scale capacity expansion in ERCOT.

The daily peak demand results from our model follow the same trends as other large-scale heat pump electrification studies. Those studies find peak demand increases ranging from 14% to 59.8% and a 1.5 GW peak demand increase per 1 million heat pumps [39–41]. Our study reflects an increase of 2.84 GW peak demand per 1 million heat pumps. This deviation from the results of these studies could be because of dissimilar building stock and more inconsistent weather in Texas. Extremely low temperatures typically drive the Texas winter peak, rather than total seasonal energy consumption.

3.1.2. County-level effects

Fig. 7 shows the change in demand per household during its respective peak hour of the year between the base scenario and the standard efficiency (Fig. 7A) or ultra-high efficiency (Fig. 7B) scenario. In general, the climate of Texas is colder in the more northern areas of the state. Thus, counties in the north and west part of the ERCOT region see the largest magnitude of change in the peak demand hour of the year because the newly electrified heating demands are higher in those parts of the state. The northwest region of ERCOT is sparsely populated and contains less electricity transmission and distribution infrastructure and a large spike in demand might require a more robust grid network. Fig. 7B shows that the increase in peak hour demand is much more moderate in the ultra-high efficiency scenario, and even decreases on average in some counties.

Because the effects of electrification occur differently according to geographic location, these findings can inform how heat pump rollouts can be implemented. For example, it is likely that the electrification of heating in the south and southeast part of the ERCOT operating region would cause fewer disruptions to the electrical system than if it was first implemented in the northwest part of ERCOT.

3.2. Electricity consumption and emissions findings

3.2.1. Annual consumption

We find that the annual electricity consumption of the electrification scenarios stays roughly the same as the base scenario for the standard efficiency scenario and decreases compared to the base scenario for the high efficiency and ultra-high efficiency scenarios. Table 2 shows the absolute energy consumption data for all scenarios and fuel sources. Although energy consumption decreases for all scenarios compared to the base, the electrification scenarios require more grid capacity than the base scenario. Fig. 8 shows a violin plot of the electricity and natural gas consumption distribution among each representative household. Note the large increase of zero-consumption natural gas households from the base scenario to the electrification scenarios as well as the similar plot shape between the base and standard efficiency scenarios for electricity consumption. Emissions from carbon dioxide and nitrogen oxides decrease in every electrification scenario because the slightly cleaner emission mix from the grid displace emissions created by residential fossil fuel furnaces. The emissions mix is expected to get cleaner in the next 10 years as ERCOT plans to add between 14 and 27 gigawatts of solar capacity [63].

Table 2
Annual energy consumption of the ERCOT residential sector over all simulation cases. The electricity consumption increase in the standard case is negligible and in all other cases energy use decreases substantially over all fuels. Natural gas and propane consumption are only reduced by approximately 50% because of gas and propane domestic water heaters, clothes dryers, lighting fixtures, pool heaters, and stovetops that continue to exist in the space heating electrification scenarios.

Scenario	Electricity (TWh)	Electric cooling (TWh)	Electric heating (TWh)	Natural gas (trillion BTU)	Propane (trillion BTU)
Base	127.1	47.5	9.2	101.6	8.5
Standard	127.1	43.2	13.4	55.7	4.6
High	119.5	36.9	12.2	55.7	4.6
Ultra-high	113.3	32.3	10.4	55.7	4.6

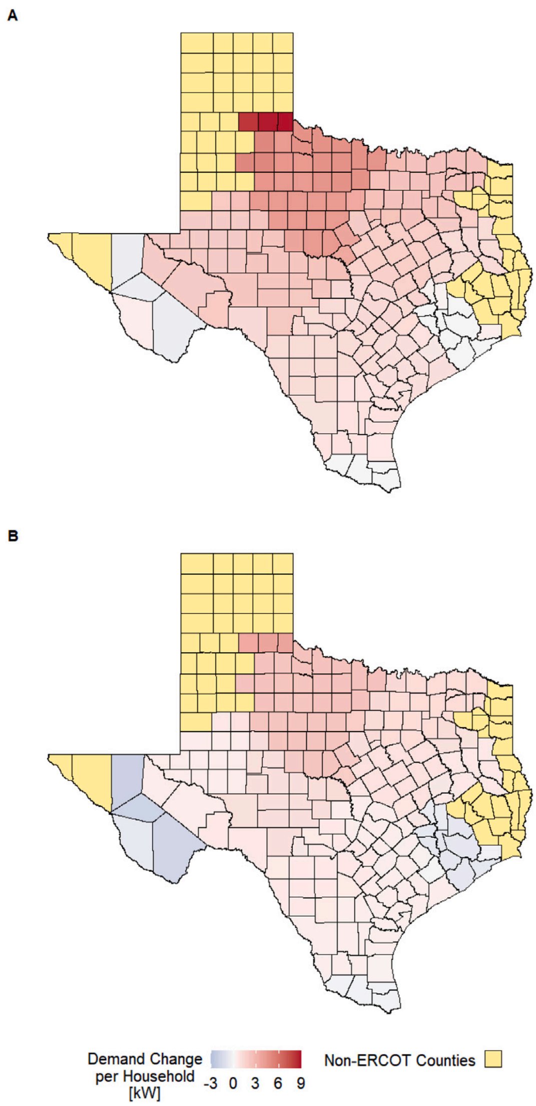

Fig. 7. Map A depicts average change in system peak hour demand per household between standard efficiency and base scenarios. Map B average change in system peak hour demand per household between ultra-high efficiency and base scenarios. This figure shows geographic differences in the magnitude of the change between the peak hour of the current building stock and the peak hour of fully electrified housing stock. The demand change magnitude follows a trend of higher change in more northerly locations, largely because of colder climates in the panhandle and northwest region of the state.

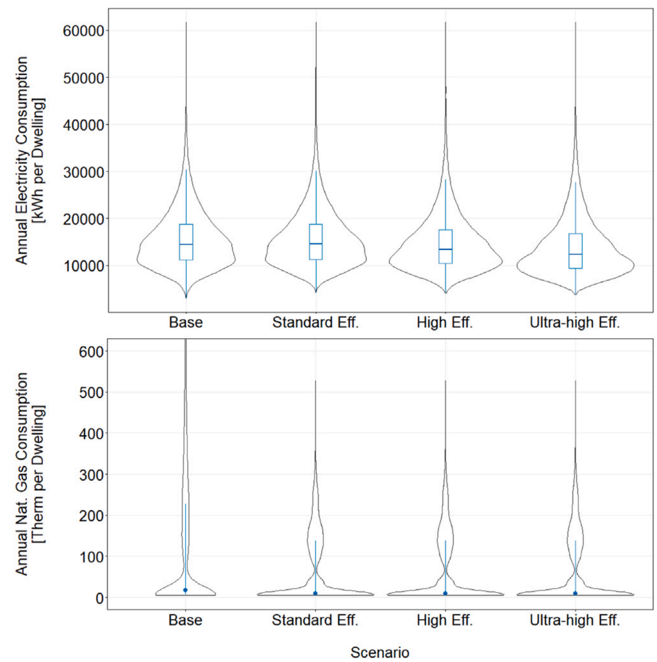

Fig. 8. Violin plots for the annual electricity and natural gas consumption for each representative dwelling. The box plot's horizontal line indicates the median electricity consumption and its length indicates the inter-quartile range (IQR). The dot on the natural gas violin plots indicate the median annual natural gas usage and the line protruding from it indicates the range from the median to the upper (0.75) quartile. To ensure readability of the plot, we reduced the Y-axis limits to 2 * the IQR of the base case's natural gas consumption.

3.2.2. Load duration curves

Fig. 9 shows load duration curves of each scenario in this study. A load duration curve portrays how many hours over a year that a certain amount of demand occurs. The lowest demand hour is on the far right, at hour 8784 (2016 was a leap year) and the peak demand hour is on the far left at hour 1. Thus, the integral of a load duration curve is annual energy consumption. The region of Fig. 9 that is most pertinent to this study is the top left where the hours of highest demand are shown. because this is what can affect an electrical grid's PRM and capacity planning strategy. The inset of Fig. 9 shows the same load duration curves over the 10 highest demand hours.

According to these data, the three electrification scenarios have lower average demand, but their peak demand hours are higher than the base scenario. Very cold weather induces a higher peak hour on the system than the base scenario, but the electric heat pumps keep average demand lower during the spring, summer, and fall months because of their higher efficiency at cooling households. This reduction in electricity use during cooling days is why the annual electricity consumption for the electrification scenarios is either the same or less than the base scenario's annual electricity consumption.

The inset of Fig. 9 shows that for the High and Ultra-high efficiency electrification scenarios, the demand only exceeds that of the base scenario for approximately five hours of the year, split across two days (as seen in Figs. 6 and 5). It is likely that demand response strategies could shift this demand to lower-demand hours. For example, internet-connected thermostats could pre-heat some homes and use their thermal mass to coast through the five peak hours on the two peak days.

Table 3
Absolute emissions and percent reduction in emissions from the base scenario's emissions across all electrification scenarios. Average total (baseload and non-baseload) emission rates: 425.5 kg/MWh for CO_2, 0.23 kg/MWh for NO_x emissions, and 0.36 kg/MWh for SO_x. Average non-baseload emissions rate: 573.2 kg/MWh for CO2, 0.36 kg/MWh for NOx emissions, and 0.5 kg/MWh for SOx. Fossil fuel heating furnace emission rates: 53.2 kg/MMBtu for CO_2, 0.04 kg/MMBtu for NO_x, and 0.00027 kg/MMBtu for SO_x. The mid-case scenario has a 2050 annual average long-run marginal CO_2 emissions rate of 290 kg/MWh, the scenario with a high projected cost of renewable energy (HCRE) has a rate of 239.2 kg/MWh, and the scenario with a low projected cost of renewable energy (LCRE) has rate of 177.3 kg/MWh.

	Residential sector emissions [thousand metric tons]				Percent reduction from base		
	Base	Standard	High	Ultra-high	Standard	High	Ultra-high
NO_x 2018	33	31	28	26	5.8%	14.1%	21.0%
SO_x 2018	46	46	42	39	0.0%	8.3%	15.0%
CO_2 2018	59,400	56,900	52,600	49,000	4.1%	11.4%	17.4%
CO_2 2050 Mid-Case	42,200	39,700	37,500	35,700	5.8%	11.0%	15.3%
CO_2 2050 HCRE	35,700	33,300	31,500	30,000	6.8%	11.9%	16.1%
CO_2 2050 LCRE	27,900	25,400	24,100	23,000	8.7%	13.6%	17.5%

HCRE = high projected cost of renewable energy
LCRE = low projected cost of renewable energy

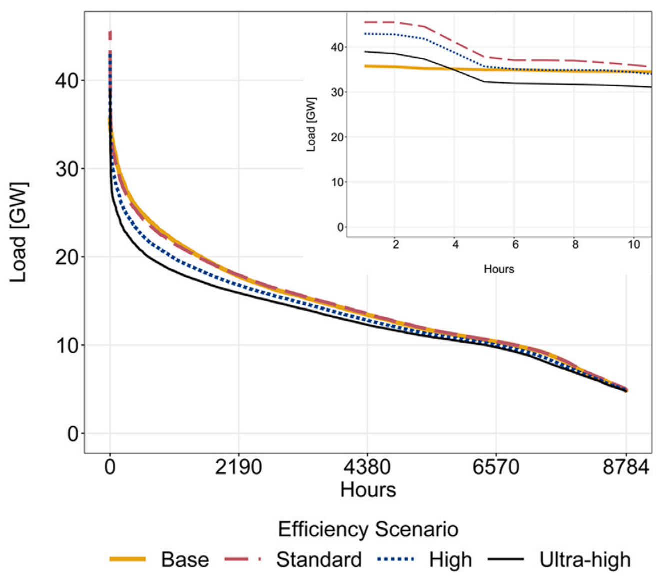

Fig. 9. Load duration curve for each scenario of electrification and the base scenario. These curves show the load required to meet every hour of the residential sector's demand from highest demand hour to lowest demand hour for each simulation case. The inset graph shows the same data, but for only the highest 10 load hours of the year. The figure shows that the electrification scenarios (pink long-dashed line, blue dotted line, and dark gray thin line) utilize the same or less amount of capacity as the base simulations case (yellow) until the most demanding hours of the year (see inset graph). During those hours, the electrification cases demand up to 12 GW more than the peak hour of the base simulation case.

Fig. 9 shows that each electrification scenario requires more demand during the few highest demand hours of the year compared to the base scenario. This likely requires the electrical grid to expand its capacity or change its supply mix to meet the increased demand during the electrification scenarios' peak hours. Peaker power plants – power plants that only turn on to meet demand during peak hours – typically have a lower efficiency than baseload power plants. For example, in 2018, ERCOT non-baseload CO_2 emission rates were 35% higher than the average emission rates [64]. This lower efficiency typically leads to peaker plants generating more emissions per megawatt-hour produced.

3.2.3. Current and future emissions analysis

Emissions calculations for this study are evaluated within two different contexts: (1) the emission reductions with respect to present-day electric and on-site combustion emissions values and (2) the carbon emission reductions with respect to a future electric grid that has in part been decarbonized. Table 3 shows the residential sector absolute emissions and percent change from the base scenario's total emissions for each electrification scenario. Present-day emission calculations for electricity are based on EPA eGRID average and non-baseload emissions rates for ERCOT in 2018 [64]. Average emission rates are used to calculate the base scenario's electricity emissions. Average non-baseload emission rates are applied to the change in electricity consumption from the base scenario and each electrification scenario. This usage of non-baseload emission rates is necessary because a widespread building stock change would be a driving force on the daily residential peak when non-baseload plants are active. The displaced emissions from replacing fossil fuel heating furnaces are derived from EPA stationary point and air sources data [65].

To estimate how these changes in emissions might change under future grid scenarios, Table 3 also includes annual CO_2 emissions reductions using annual average long-run marginal emission rates for three 2050 scenarios from the NREL Cambium dataset, which provides data from capacity expansion and generator dispatch modeling for 2020 Standard Scenarios [66]. The long-run marginal emission rates consider socio-technical drivers like population growth and increased residential demand.

Ideally, one would know the marginal emissions for the generation mix at different hours of the year, for years into the future; however, changes in load of this magnitude would require further modeling of capacity expansion or supply dispatch, which is beyond the scope of this study. Using average emissions data is sufficient to estimate coarse directional impacts. Because the annual electricity consumption is not increased in any of the electrification scenarios, emissions decrease for each electrification scenario. This emissions reduction occurs because fossil-fuel furnace emissions are getting replaced while no increase in electricity usage occurs. True emissions reductions of an electrified residential sector will depend on a future emissions mix that likely falls within the bounds of the 2050 scenarios' long-run marginal emission rates, a percent reduction between approximately 6 and 9 percent for the standard efficiency scenario.

4. Conclusions

In this analysis, we utilized NREL's ResStock and the open-source EnergyPlus tools to quantify the electricity usage of a residential sector with 100% electrified heating. The results show how an electrified residential sector in Texas would peak in the winter instead of the summer. This switch would likely decrease net emissions while also requiring the grid to increase its capacity to accommodate higher spikes in demand during the winter months.

The electrification of space heating in the ERCOT residential sector would shift the residential sector from peaking its demand in the summer to the winter. In our analysis, annual electricity consumption does not increase because the more efficient heat pumps reduce the summer cooling energy use more than they increase winter heating energy demand, but the electric grid may need to increase its total generating capacity to accommodate very high demand during extreme cold weather events.

This study is useful to grid planners and policy makers, particularly those in regions primarily driven by summer cooling loads, because it gives insights into the grid impacts of heating electrification programs and policies. Such insights are to expect a higher residential winter peak demand and lower residential summer demands. Our analysis also showed how the change in demand can vary across large-scale synchronous electric grids and thus how a specific electrification policy can have various localized impacts. This information is critical for the smart deployment of grid resources. The methodology herein could be expanded to other regions to explore the impacts of space heating electrification on other large-scale synchronous electric grids.

CRediT authorship contribution statement

Philip R. White: Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Joshua D. Rhodes:** Conceptualization, Writing - review & editing. **Eric J.H. Wilson:** Methodology, Resources, Validation, Writing - review & editing. **Michael E. Webber:** Supervision, Writing - review & editing, Project administration.

Declaration of competing interest

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

Data availability

Datasets related to this article can be found at http://dx.doi.org/10.17632/v8mt9d3v6h.1, hosted at Mendeley Data (White et al. 2021).

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