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Reevaluating Texas Energy Market Forecasts in The Wake of Recent Extreme Weather Events

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Abstract. This paper provides updated forecasts of energy demand in Texas and recognizes the impact of sustainable energy. It is important that the forecasts of the adoption of sustainable energy are reexamined after Winter Storm Uri crippled the Texas power grid and left many without power. This storm highlighted the issues the Texas power grid had and has continued to struggle with in supplying the state with energy. This paper will offer an overview of the relevant literature on the adoption of sustainable energy and relevant events that have occurred in the state of Texas that will give the reader the necessary background and context needed to understand the need for this study as well as its implications. The text will offer the reader updated forecasts with respect to the increasing adoption of renewable energy in Texas. Two major methodologies will be addressed as the researchers used different forecasting techniques to produce the most accurate model for forecasting the total energy demand for all the areas that ERCOT services. The discussion will review the findings of the forecasting methods used, the significance of the findings, and the implications of the results for the future of the Texas energy economy.

1 Introduction

As the global community grapples with the urgent need to mitigate climate change, the transition from fossil fuels, pivoting to renewable energy has emerged as a crucial strategy. A major challenge that must be overcome in the implementation of this strategy is the forecasting of the demand for energy so that the need can be met readily. The shift to sustainable energy sources is particularly pressing in Texas, where the effects of climate change, exemplified by extreme weather events like Winter Storm Uri, underscore the necessity of moving away from traditional energy sources towards sustainable alternatives. This review delves into the multifaceted landscape of sustainable energy in Texas, with a specific focus on predicting total daily energy demand as a cornerstone for effective energy grid management and resilience planning.

Recent events, such as Winter Storm Uri and the subsequent challenges faced by the Texas power grid, have highlighted the urgency of reevaluating forecasts of energy demand and supply. The unpredictability and severity of weather patterns, exacerbated by climate change, necessitate updated forecasting methodologies to ensure grid reliability and resilience. The performance of ERCOT, Texas' primary grid operator, in managing these

challenges has also come under scrutiny, further emphasizing the need for accurate and timely forecasts to inform policy decisions and infrastructure investments.

Forecasting total daily energy demand involves complex considerations, including the interplay between renewable energy generation, energy storage capabilities, and evolving consumer behaviors. Recent research has leveraged advanced modeling techniques, such as K-Nearest-Neighbors (KNN) space-time simulation and machine learning algorithms, to enhance the accuracy of energy demand forecasts. These approaches consider factors such as weather patterns, infrastructure resilience, and policy dynamics to provide more nuanced predictions of energy demand, crucial for effective grid management.

Harnessing Texas' abundant solar and wind resources is central to the state's sustainable energy transition. Studies have explored the performance characteristics of solar concentrators and evaluated hierarchical methodologies for assessing solar energy availability under different sky conditions. Similarly, advancements in wind energy technology have underscored the economic and environmental benefits of wind energy projects in Texas.

Energy storage and grid integration are critical components of a resilient energy infrastructure. Research has focused on developing grid-scale energy storage solutions, including advanced batteries and pumped hydro storage, to ensure a consistent energy supply during extreme weather events and periods of low renewable energy generation. Policy dynamics and incentives also play a crucial role in driving the transition to sustainable energy in Texas, with studies highlighting the impact of renewable energy tax incentives on electricity pricing and the importance of inclusive policy frameworks for empowering vulnerable consumers. In conclusion, predicting total daily energy demand is essential for guiding policy decisions, infrastructure investments, and grid management strategies in Texas' transition to sustainable energy.

2 Literature Review

The transition from fossil fuels to clean and renewable energy sources has emerged as a promising solution to mitigate climate change's detrimental consequences. As the effects of climate change become increasingly apparent, the imperative of Texas to shift away from traditional energy sources towards sustainable alternatives grows ever more pressing. This review delves into the multi-faceted landscape of sustainable energy in Texas, encompassing renewable energy assessment, policy dynamics, infrastructure resilience, grid reliability, and the integration of cutting-edge technologies. It sheds light on the state's remarkable potential to lead the way in building cleaner, more reliable, and accessible energy systems for a sustainable future.

In this comprehensive exploration, this paper discusses the harnessing of Texas' abundant solar and wind resources, examines the resilience of its energy infrastructure in the face of extreme weather events, investigates the catalytic role of government policies and incentives in the transition to sustainable energy, analyze the intricate balance between energy supply and demand, and delve into the latest advancements in sustainable energy technologies. By probing these diverse facets of sustainable energy, Texas seeks to safeguard its energy future and contribute to a global movement toward a more sustainable and resilient world. Let's dive into the detailed sections that elaborate on each of these key points.

2.1 Reevaluating Environmental Drivers for Forecasting

At the time of the research for and writing of Mann’s team’s 2017 paper [17], Winter Storm Uri wouldn’t happen for another 2-3 years. Occurring in February of the second year of a global pandemic, Uri’s frigid low temperature of 6° F specifically in Austin, Texas, and the same number of inches of snow that broke the “record for consecutive days of snow on the ground” [29] blindsided Texans in that way for the first time in several years, and for the last time ever for 210 of those people. Nearly 70% of Texans had no power for the six days spanning February 14th to the 20th [26]. In Germany, just five months later, part of a castle erected in the 1800s was washed away by a nearby river flooded by astonishing rainfall in the region [9]. In the summer of 2023, residents of North America either sneezed, coughed, or choked on the smoke of unprecedented wildfires across much of Canada [24], and in the historical community of Lahaina on the Hawaiian island of Maui, high winds gusting up to hurricane velocity were whipped up by an actual hurricane passing the archipelago to the south. These winds tore down power transmission lines onto dry lawns and began a surprising and horrific wildfire that destroyed the town [14] and the lives (fully destroyed, i.e., ended) of over ninety residents. In the same late summer months, ERCOT struggled to keep the Texas power grid from failing again, this time not for extreme cold but rather extreme heat [10]. It can go without saying that these recent developments in the Earth’s weather have motivated a sense of urgency in some about the timeline and coming effects of climate change, and that the performance of ERCOT over the past few years has shaken Texas residents’ confidence in its ability to maintain grid integrity [15]. It is because of this urgency that, despite Mann et al. 2017 giving forecasts through 2030 (Figs. 22-35, Table 10, etc.), this study goes, to quote Shakespeare, “once more unto the breach” of the issue to reevaluate such forecasts with the most recent data on grid conditions, assuming those conditions are affected by climate change-related weather patterns and phenomena, by the ability of renewables (most notably those affected by weather and/or atmospheric conditions, namely, wind and solar) to support the demand placed on the grid, and by forces of economic and governmental policy conditions and decisions.

Fortunately for researchers investigating this topic, summer peak demands on ERCOT’s grid are relatively stable compared to a linear regression model, with actuals visibly closer to their regression line than the same for winter peak demands [22]. Skiles’ team finds these results are from a variety of reasons, including summer demands being influenced by notable efficiency in electric cooling and winter demands being volatile on account of, in part, the transition of home heating from natural gas furnaces to electric heat pumps and the like. Axiomatically, the use of natural gas furnaces in homes, while common for heating, makes little sense applied to cooling, so an analogous home-heating appliance transition would not be reflected in summer demand data. With this winter demand variability and the possibility of more century storms like Uri happening on the order of decades or shorter (recall the 2011 blackouts in Texas also caused by winter storms), ERCOT has clear cause to cultivate versatile power generation solutions to address the need for easily dispatched generators or energy storage units that are robust in near-zero-Fahrenheit weather that may include dangerous and/or damaging precipitation like freezing rain. Winter weather, however, does not and will likely not maintain a monopoly on

ERCOT's struggle to avoid capacity-deficit blackouts. Markham Watson refers in his article to an announcement from ERCOT stating that despite "that there will be sufficient installed generating capacity available to serve the system-wide forecasted peak load for the upcoming summer season, June-September 2023", "for the first ... time the peak demand for electricity this summer will exceed the amount we can generate from on-demand dispatchable power"; Public Utility Commission of Texas (PUC) Chairman Peter Lake warned that Texas "faces a new reality" in the summer of 2023". Lake further indicated that renewable energy would be crucial—nay, truly indispensable—to the Texas grid for summer 2023. Emily Foxhall's article in the Texas Tribune relates the stress the grid indeed faced, discussing in the article summary that ERCOT's conservation requests were at least as frequent at one point as three requests in a single week.

During the February 2021 Texas energy crisis, natural gas prices spiked so extremely that the state government was forced to place price caps and utilize other market controls to prevent said market from suffering a meltdown from the sheer volatility caused by a perfect storm of gas plant and wind turbine failures; some of the gas plant failures were accidents, occurring when electricity transmission providers were asked to suppress transmission to avoid damage to the heavily in-use grid. This action "pulled the rug out from under" the gas supply chain installations on those providers' grid subdivisions, causing them to fail by starvation of their operational electricity requirements for getting the natural gas through the supply chain to the plants that would do the actual power generating using the gas. In a grimly amusing way, the Texas natural gas infrastructure was essentially *asphyxiated* [6]. Solar power, on the other hand, performed as well as could be expected [25], giving hope to the notion that it can be the MVP (Most Valuable Producer, if you will) of winter demand satisfaction in a renewable energy future, whereas the delay of summer daily demand ramping down later than solar production ramps down [8] precludes that advantage in summer months without clever application of batteries, and perhaps not even then.

2.1 Political and Social Drivers

Dismayingly for virtually any American citizen and foreign national paying close attention to American politics and concerned about the effects of fossil fuels on these changes in the climate that our power grids must protect us from, the Republican Party (GOP) as a whole is well known for their dogged support for fossil fuels and especially in conjunction with its dogged support for the business interests of major corporations. The governor of Texas during Winter Storm Uri's aftermath was Greg Abbott, a leading politician of the GOP as the governor of a state long associated within & beyond U.S. borders with American conservative & right-wing politics. It is no surprise, then, that under his guidance initiatives begun immediately following the energy disaster caused by Uri gave priority to natural gas generation. This aligns with the preference to utilize fossil fuels for energy, and to the business interests of members of the natural gas and other fossil fuel industries in Texas. Keeping in mind how various segments of the Texas energy market performed during the crisis. We recall that gas generation and gas infrastructure failed, in addition solar and wind saw significant failures as well during the storm. According to Mann's paper, current natural gas generation as of 2015 contributes well over three times the amount of

electricity to the ERCOT grid that wind does. That said, solar currently contributes such a small amount of the total Texas power supply that much more investment in its infrastructure is needed to allow it to effectively combat adverse grid conditions.

A year after Uri, the majority of Texans polled by the Texas Politics Project were unsatisfied with their state government's response to the energy disaster [19]. Investor interest in fossil fuel power generation has fallen well behind renewables and other clean energy forms such as the Comanche Peak nuclear plant [8]. The desires of the people and the prevailing winds of the energy economy demand certain actions be taken by responsible parties. ERCOT's reputation as custodian of the Texas electric grid, and its responsibilities as an extension of the state's government have not adequately met the actions required. Measurably counterproductive decisions such as this coming from places of power are a notable detractor to the successful implementation and maintenance of new and existing renewable and clean energy generators. Regarding public support for and participation in the renewables market, hope for the transition of energy generation away from fossil fuels remains. ERCOT and the State of Texas would be more helpful to those ends if they encouraged and facilitated such investments in more sustainable energy solutions. Nevertheless, the renewables economy already benefits from government encouragement for new technologies and infrastructure types: at the federal level, for example, standalone storage facilities (no generation, only storage), which in today's economy benefit from significant strides in battery technology in recent years and from other novel energy storage means, benefit from a whopping 30% investment tax credit (ITC) specifically for such facilities [8]. As gas- and especially coal-fired power plants age less than gracefully and are gradually left behind by the economy, a total of 18.3 gigawatts (GW) of renewable energy capacity is in development for the Texas grid, driven strongly by these federal tax credits.

Happening similarly on another front, as of October of 2022, experts in the energy field had reason to believe that ERCOT would not be ready for another Uri. The executive director of Commission Shift, Virginia Palacios, is referenced in Justin Horwath's 2021 article that the Texas Railroad Commission (TRC) had not physically inspected (i.e., with TRC representatives physically on-site for the inspections) most of the gas supply chain installations under its jurisdiction, despite the TRC stating that nearly all inspected facilities were sufficiently winterized [13]. At best it can be inferred that the TRC suffers from lax standards of inspection and frustrating budgets; at worst TRC's statements can be viewed as purposive platitudes, dispensed to lull the public into the belief that the Texas government is doing its job to ensure grid reliability when in fact little more than lip-service is being done. However, as mentioned before, if the statements discussed were indeed meant as platitudes, they haven't convinced Texans [19]. This is not to say that the Texas grid has not been improved. Energy industry consultant Alison Silverstein relates in Horwath's article that the standards placed on power plants for their weatherization have been made more stringent and that policy changes have been implemented to prevent the sort of severe price spikes that, along with ice and snow, were precipitated by Winter Storm Uri.

The combination of a hazardous push to invest more in fossil fuel combustion for generating power for Texas' grid and an inadequate response to patent faults in ERCOT's management of the grid and the natural gas supply chain laid bare by Winter Storm Uri show that there is good cause for concern regarding the integrity of the Texas power grid in the near future and the effects its provision, use, and management may have on the global climate and the safety of the vast majority of Texans. The scientific community and the public cannot afford to be complacent with forecasts of grid conditions and climate

perils made even five years ago: the situation has changed and with it so must the schedule of analysis.

2.3 Sustainable Energy Assessment: Harnessing Solar and Wind Resources

Texas, recognized for its vast solar and wind resources, stands as a prominent player in the transition to sustainable energy sources. Akhadov's research in 2023 delves into the performance characteristics of solar concentrators, shedding light on the potential of solar thermal energy production [1]. By examining the efficiency and effectiveness of solar concentrators, this study contributes to harnessing solar energy in Texas, a state that enjoys abundant sunlight throughout the year. The findings emphasize the importance of improving and optimizing solar energy technologies to make the best use of Texas' solar potential [1].

Al-Aboosi (2019) introduces hierarchical methodologies for evaluating solar energy availability under different sky conditions, with Texas as a significant case study [2]. This research illuminates the dynamic nature of solar energy generation due to Texas' diverse climate. By studying how solar energy varies under various sky conditions, this work provides insights into optimizing the use of solar panels and ensuring a consistent energy supply, even in challenging weather scenarios. It highlights the significance of understanding the factors that affect solar energy availability for better energy planning and infrastructure [2].

Amonkar et al. (2022) introduce a k-nearest-neighbor space-time simulator for wind and solar power modeling, contributing to the integration of renewable energy sources on a large scale [3]. The innovative approach presented here facilitates a more accurate prediction of wind and solar energy generation. By using space-time simulation, researchers can make precise forecasts, which are crucial for optimizing energy grid management. It provides a foundation for understanding when and where renewable energy sources will be most productive, aligning supply with demand more effectively [3].

Slattery et al. (2011) emphasize the state and local economic impacts of wind energy projects, providing valuable insights into Texas' wind energy continuing economic benefits [23]. Texas, with its extensive land area and favorable wind conditions, holds significant promise for wind energy. This research not only highlights the economic advantages of investing in wind energy but also showcases the positive environmental impact by reducing greenhouse gas emissions [23]. By understanding the local economic benefits, policymakers can make informed decisions to support the growth of wind energy in Texas.

2.4 Energy Storage and Grid Integration

While Texas possesses vast solar and wind resources, the variability of these renewable energy sources necessitates efficient energy storage solutions. Energy storage is a crucial aspect of sustainable energy infrastructure. Researchers like Zhang et al. (2022) focus on the complexities of energy grid failures, but it's equally vital to explore how energy storage can mitigate such failures [30]. Texas must invest in grid-scale energy storage technologies such as advanced batteries, pumped hydro storage, and compressed air energy storage. Systems such as these store energy in a variety of chemical and mechanical ways, holding

in reserve electrical power to supplant power being generated in real time when the latter is incapable of supporting consumer demand with a safe margin [30].

The integration of energy storage solutions into Texas' grid is pivotal. It ensures a consistent energy supply even during severe weather events or when renewable energy generation is insufficient. Policymakers and energy providers need to collaborate on creating incentives for the development and deployment of energy storage systems, as this is essential for achieving a reliable and resilient sustainable energy infrastructure.

2.5 Infrastructure and Resilience: Preparing for Severe Weather Events

Texas' energy infrastructure faces resilience challenges, as demonstrated by the severe disruption caused by the 2021 Winter Storm Uri. The Texas Comptroller of Public Accounts conducted a comprehensive economic assessment of the storm's impact, revealing vulnerabilities in the state's energy infrastructure [26]. The study provides a comprehensive analysis of the economic consequences of severe weather events on energy infrastructure. It underscores the need for proactive measures to enhance grid resilience, as disruptions like Winter Storm Uri expose vulnerabilities in the system [26]. This research is instrumental in guiding infrastructure investments and improvements to withstand extreme weather conditions.

Zhang et al. (2022) conducted a detailed analysis of the causes and consequences of the 2021 Texas blackouts, elucidating the complexities of energy grid failures and their mitigation [30]. By analyzing the root causes and the subsequent impacts of the Texas blackouts, this research provides valuable insights into grid management and disaster response. Understanding the intricacies of energy grid failures is essential for designing effective mitigation strategies and improving overall grid reliability [30].

2.6 Policy & Incentives: Catalysts for Sustainable Energy Transition

Government policies and incentives play a pivotal role in Texas' transition towards sustainable energy. Hanke et al. (2020) explore empowering vulnerable consumers to participate in renewable energy communities. Their research highlights the inclusive design of the Clean Energy Package, a policy framework that makes sustainable energy accessible to a broader population. By focusing on community involvement, this study promotes the idea that sustainable energy should be accessible to all, irrespective of socioeconomic factors. It underlines the importance of supportive policies to drive the transition to sustainable energy in Texas [12].

Rudolph et al. (2023) investigates the impact of renewable energy tax incentives on electricity pricing, demonstrating the intricate relationship between policy measures and energy costs. Their research highlights how government incentives can significantly affect the affordability of sustainable energy for consumers. By analyzing the effects of tax incentives, this study offers valuable insights into the interplay between policy decisions and the economic aspects of sustainable energy adoption [20]. It highlights the significance of well-structured policies in making sustainable energy an attractive choice for consumers [20].

2.7 Balancing Energy Supply and Demand

Balancing energy supply and demand is vital for a resilient energy grid. Bixler et al. (2019) developed an observatory framework for understanding urban social-ecological-technical systems. This framework enhances comprehension of the dynamics between energy supply and demand, providing valuable data for policymakers and energy providers. By studying the interplay between several factors in urban systems, this research offers insights into managing energy supply and demand efficiently. It contributes to the development of strategies for maintaining a stable and reliable energy grid [5].

2.8 Modeling Energy Forecasting and Demand

Amonkar (2022) KNN space-time simulator research highlighted assessing the severity, duration, and frequency of energy droughts in the Texas Interconnection. His research incorporates the spatial structure and wind-solar dependence in simulations, providing a tool for estimating the regional long-duration storage capacity. The research highlights the significance of correctly representing space-time dependence in simulations to ensure accurate estimations in the context of wind and solar generation configurations [3].

Utilizing Random Forest Regression (RFR) and Long Short-Term Memory (LSTM) models Balal's (2023) research focused on forecasting solar photovoltaic (PV) power generation in Lubbock, Texas, these models exhibit the capability to capture intricate patterns and complex relationships in solar power generation data, providing valuable insights for solar PV investors in improving planning and production processes. Their study emphasizes the suitability of machine learning models, particularly ensemble methods for accurate solar PV power generation forecasting [4].

Employing ARIMA, Multiple Linear Regression, and Seasonality models, Ruthford's (2021) time series-focused study forecasts electric energy demand. The study does a robust job highlighting notable deviations from a simple sinusoidal pattern due to several factors by combining ERCOT demand with weather data. The time-series models were developed to account for these seasonal factors, utilizing one-hot-encoded variables for month, day, and hour, along with the compiled temperature data [21].

2.9 New Technologies for Sustainable Energy

Technological advancements are driving the sustainable energy transition in Texas. Mekhilef et al.'s comprehensive review in 2011 of solar energy use in industries highlights the role of technology in the industrial sector. Their findings emphasize the importance of adopting advanced technologies to enhance the integration of solar energy into various industrial processes. This research showcases the potential for technology to revolutionize industrial energy usage in Texas [18].

Woo et al. (2023) explore regional revenues from solar and wind generation, emphasizing the economic potential of new technologies, including advanced weather modeling and improved solar and wind technologies. Their research provides a detailed economic perspective on the adoption of these technologies in Texas [28]. By highlighting the economic benefits, it underlines the promising outlook for sustainable energy technologies in

the state. This research also signifies the role of advanced weather modeling in optimizing the use of solar and wind energy, making it more reliable and efficient [28].

3 Methods

The demand for electricity is a pivotal driver of modern society, underpinning a wide range of essential activities, from powering homes and industries to supporting technological advancements and environmental sustainability. Accurate and reliable models of electricity demand are paramount for grid management, resource allocation, and the development of sustainable energy policies. In this literature review, this study embarks on a comprehensive exploration of methodologies used to model electricity demand, with a specific focus on data sourced from the Electric Reliability Council of Texas (ERCOT) spanning the years 2007 to 2023.

Electricity demand modeling has gained substantial importance in recent years due to the increasing complexity of energy markets, the integration of renewable energy sources, and the need for efficient resource management. ERCOT, as the independent system operator for the Texas electricity grid, offers a rich dataset that encapsulates diverse and dynamic factors influencing electricity consumption.

This section's main intent is to explore and analyze the diverse modeling approaches that researchers have used to understand and predict electricity demand within the ERCOT region. Two major modeling paradigms are considered in detail: Linear Modeling and Time Series Models. Each of these approaches offers unique advantages and exhibits limitations in its capacity to capture the nuanced behavior of electricity demand data. The overarching goal is to evaluate the suitability of these modeling techniques in the context of ERCOT data and, by extension, contribute to the body of knowledge surrounding energy demand modeling.

Throughout this review, the discussion will delve into the strengths and weaknesses of each modeling approach, highlighting their ability to account for temporal dependencies, capture non-linear patterns, and provide interpretable insights. Moreover, it will examine how these models handle the intrinsic complexities associated with electricity demand forecasting, such as seasonality, volatility, and unforeseeable external factors. In doing so, this paper aims to guide future research endeavors, inform policy decisions, and assist energy stakeholders in their efforts to optimize resource allocation and grid management within the ERCOT region.

Understanding and accurately predicting electricity demand hinges on a myriad of factors, from seasonal variations to unforeseen fluctuations influenced by external forces. However, the inherent unpredictability of weather patterns poses a significant challenge to achieving perfect knowledge in this domain. Weather conditions play a pivotal role in shaping energy consumption, affecting everything from heating and cooling needs to outdoor activities that impact overall demand. Despite advancements in modeling techniques, the inability to precisely forecast weather phenomena introduces inherent limitations to the accuracy of electricity demand forecasts. We must grapple with the reality of imperfect information, recognizing the need for robust modeling approaches that can adapt to changing environmental conditions. By both acknowledging and addressing the constraints imposed by imperfect weather knowledge, stakeholders can better navigate the complexities of energy demand forecasting and contribute to the resilience and sustainability of electricity systems within the ERCOT region and beyond.

As electricity demand continues to evolve and adapt to an ever-changing landscape, it is essential to harness advanced modeling techniques that can respond to the multifaceted challenges of the energy sector. This paper serves as a comprehensive reference for researchers, policymakers, and industry professionals seeking to gain deeper insights into the modeling of electricity demand, with the goal of enhancing the sustainability and efficiency of energy systems in the ERCOT region.

3.1 Data Preprocessing

In this paper, we used two sources for our raw data. The first was the ERCOT fuel mix report for the years 2007 through 2022. 2023 data was excluded as the year was not yet complete during the beginning of this research paper and the team wanted to only consider years that had been completed. The data format had fuel type and date as the unique identifiers for each record with the features being the power demand of the fuel in a 15-minute increment. Throughout the years the naming convention underwent minor changes, and some years daylight savings time was recorded and some years it was not. It should also be noted for compatibility's sake that the files for years 2007- 2015 were of the XLS filetype, and 2016-2022 were of the XLSX type.

The second data source was the weather data from the major city airports in each of the eight ERCOT regions. Houston was used for the coastal region, Corpus Christi was used for the southern region, Lubbock for the north region, Midland for the far west region, Tyler for the east region, Austin for the south-central region, Abilene for the west region, and Dallas for the north-central region. For each region, we have a historical record of the maximum, average, and minimum readings for many weather-related conditions such as humidity, wind speed, pressure by inch, temperature, and precipitation.

Table 1: This table shows a snippet of the raw data from the year 2007. It is important to note that not all the raw power data was formatted the same way but due to the relative similarity further examples would be redundant.

Raw Power Data Snippet			
Date - Fuel	Daily MWH	0:15	0:30
01/01/07 - Coal	314608.64	3376.33	3368.08
01/01/07 - Gas	272456.95	2250.33	2252.73
01/01/07 - Hydro	688.96	3.81	3.809214
01/01/07 - Nuclear	120060.02	1250.25	1249.94

Data preparation and preprocessing is undoubtedly an arduous process in any project; in our case; this was a very laborious task to clean the data into a consumable format. Firstly, we developed a script that would take the data from the shape it came in, and transpose it into a more conducive format, having each record represent a 15-minute increment of a given date with the features being fuel type, demand for the given 15-minute increment, the Mega-Watt-Hours total for the full day. Each year of data from 2007 to 2022 was loaded into a *pandas* data frame for transposing, many years needed to be brought into a standard format so they could be appended to the pre-transposed data frame. After

this, the data frame was transposed record by record with each transposed record being appended to the bottom. A hash index was used as a unique identifier for the records in this script. The final output of the script is then exported to a csv for further cleaning.

Next, a script was developed for the purpose of cleaning the data. First, the dates were standardized to use the data type of DateTime and converted to the format MM-DD-YY. Next, the demand for daylight saving time was dropped. The decision to drop the daylight-saving data was because the data failed to always capture demand during the changeover, so the team thought it appropriate to keep the data as consistent as possible from year to year. This was achieved by creating a column called day count which would count the 15-minute intervals of the given day and then dropping all the records with a day count greater than 96. The names of fuel types were then standardized into their normal names, an example being changing “Wnd” to “Wind.”

Table 2: This table shows a snippet of the power data after all transformations have been performed. This format is both more conducive to the form the researchers needed the data to be but also is standardized and clean to be utilized in modeling efforts.

Desired Outcome of the Power Data				
Date	Time	Fuel Type	Demand	Daily Total by Fuel Type
01/01/07	0:15	Coal	3376.33	314608.64
01/01/07	0:30	Coal	3368.08	314608.64
01/01/07	0:45	Coal	3365.00	314608.64
01/01/07	1:00	Coal	3364.70	314608.64

After this, the weather data was joined to the cleaned power demand data. We compiled a historical accounting of weather data from different regions within the ERCOT network. The script merges the filtered power generation data with the weather-related data that was scraped from online sources. This integrates both datasets to form the primary dataset used in our analysis and modeling efforts. Following the merge, the script converts demand into a float, dropped the null records, and drops the day count and ‘drop?’ columns. Finally, the output is saved as a csv for later use.

The data cleansing activities combined in the script developed, orchestrates a meticulous process of data loading, standardization, transformation, merging, cleaning, and refinement, culminating in a clean and enriched dataset primed for in-depth analysis and interpretation of power generation patterns and trends.

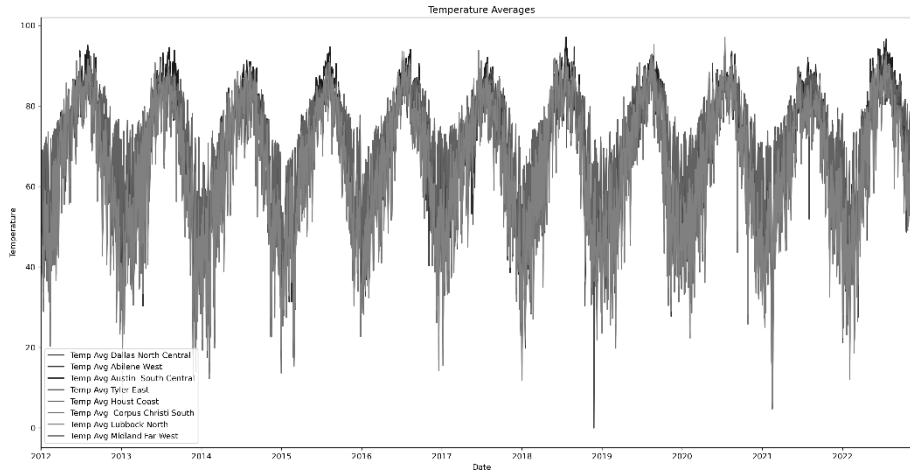


Fig. 1. This graph illustrates the historical average temperatures extracted from the Electric Reliability Council of Texas (ERCOT)'s eight distinct regions, collected from local airports within their respective areas. Though the temperature is cyclical, there are more spikes in extreme temperatures as we progress over time. By analyzing these temperature trends, we gain insights into the climatic variations experienced across ERCOT's regions over the specified period examined 2012 - 2022.

4 Results

In the next section, we focus on the two primary modeling methods utilized in our study of predicting total energy demand across ERCOT's grid. Linear models are widely employed in industry for their interpretability and computational efficiency, offering valuable insights into relationships among variables such as weather conditions and energy demand. Despite their advantages, limitations arise when assumptions of linearity are not met, as we observe in our modeling efforts. We examine the performance of linear models in predicting total energy demand, leveraging historical energy demand data and historical weather variables across eight regions. We rigorously evaluate various linear modeling techniques and acknowledge their limitations in capturing complex non-linear patterns and temporal dependencies. Additionally, we explore the efficacy of time series modeling through an ARIMA model, aiming to enhance predictive accuracy and address shortcomings observed in linear models. This section provides a comprehensive analysis of both linear and time series modeling approaches, offering insights into their respective strengths and limitations in forecasting energy demand within the ERCOT network.

4.1 Linear Modeling

Linear models are widely used in industry due to their transparent interpretability and computational efficiency. As noted previously, one of the primary advantages of linear models lies in their interpretability. They provide clear insights into the relationships between independent variables, such as weather conditions and temperature. Moreover, their simplicity and computational efficiency make them an ideal starting point for modeling tasks, allowing for swift analysis and decision-making processes. Additionally, linear models tend

to exhibit stability when the relationships between variables are linear, providing more robust predictions.

However, there are some limitations of linear models that we need to acknowledge. Inherently we assume linearity in the relationships among the features compiled in the models, this does not always hold true in real-world scenarios, as we have uncovered in our case. We found that there were some linear relationships among the features, though to varying degrees. Electricity demand data, our target variable exhibits complex, non-linear patterns influenced by numerous factors not currently captured in our models like economic conditions, technological advancements, and societal behaviors. Moreover, linear models may struggle to capture the intricate seasonality and temporal dependencies inherent in time series data, potentially leading to suboptimal predictions.

We focused on examining the linear relationships with predicting total energy demand by combining ERCOT historical demand data and collecting weather-related data from one city with an airport from each of the eight ERCOT regions. In this analysis we implemented several different linear modeling techniques. Employing a multiple linear model, five-fold cross validation, time series split, and holdout validation to understand and predict total energy demand patterns given historical weather patterns across ERCOT network.

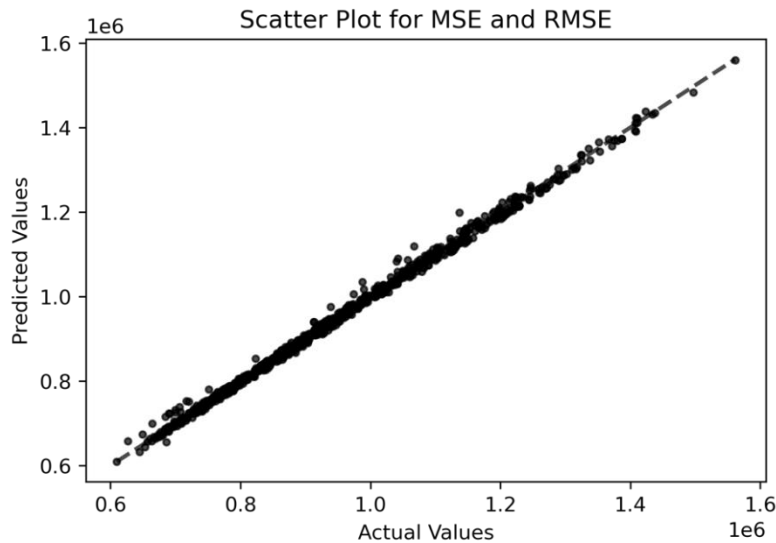


Fig. 2. This figure shows us the close alignments of points with the diagonal line suggesting that the relationship between MSE (*Actual Values*) and RMSE (*Predicted Values*) is consistent across the dataset and models. This consistency implies that the errors are evenly distributed across the dataset and that

the RMSE provides a reliable measure of the average error. The clustering of points around the diagonal line suggests the model's predictions closely match the actual values for most cases

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_{true,i} - y_{pred,i}}{y_{true,i}} \right| \times 100$$

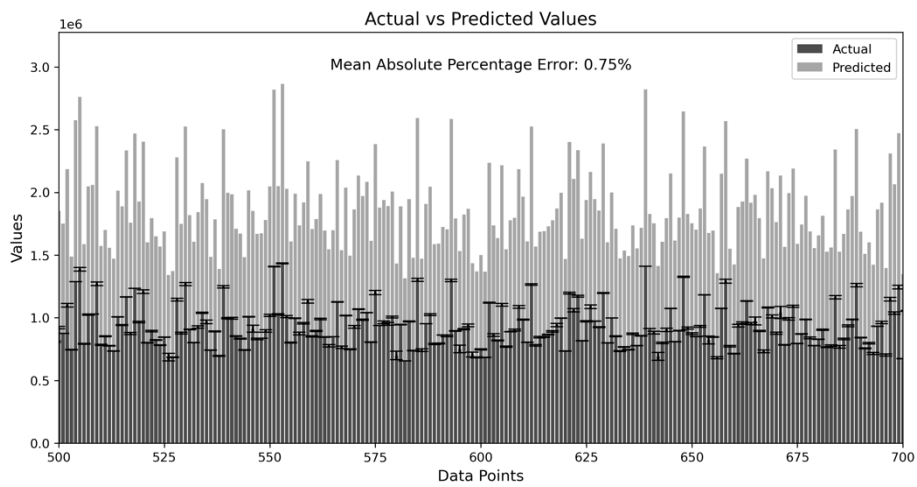


Fig. 3. The Mean Absolute Percentage Error (MAPE) is a metric used to evaluate the accuracy of a model's predictions, particularly in the context of regression. It represents the average percentage difference between predicted values and actual values with each datapoint representing a given day. Concerning our primary linear model, the MAPE of 0.75% means that, on average, our model's predictions are off by approximately 0.75% relative to the actual values. The error bars in the stacked bar chart above show the variance between predicted vs actual values on any given time. This is a subset of all data points validated against an original 0 – 800 scale.

Table 3. The Models Scores are available between the various linear models tested to predict total energy demand utilizing an 80/20 train test split dataset.

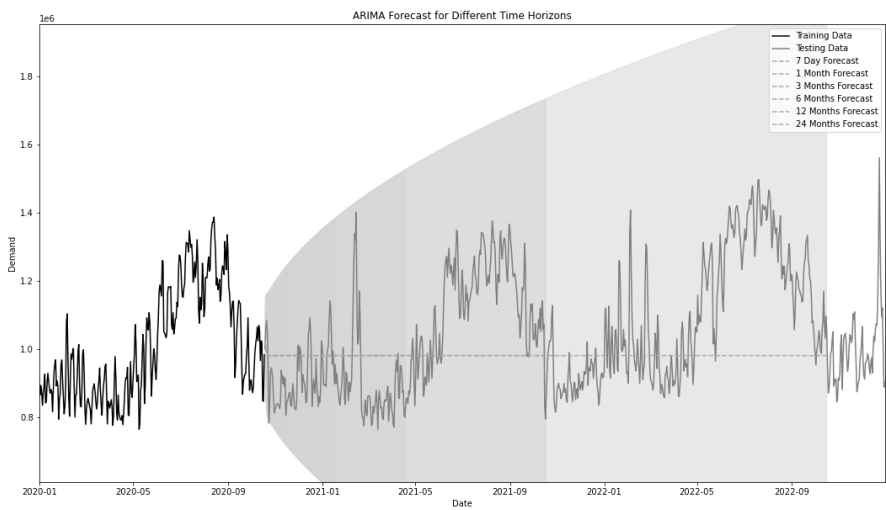
Linear Model Evaluation				
	Linear Model	Time Series Split Model	Cross Validation Model	Hold Out Model
Mean Absolute Error	7,092.04	7,495.40	7,086.11	6831.24
R ² Score	0.9968	0.9971	0.9970	0.9969

Root Mean Squared Error	9,878.40	9,344.33	9,623.54	9,568.92
Explained Variance Score	0.9968	0.9972	N/A	N/A

As noted in Table 3, the performance of the selected linear models was rigorously evaluated using standard metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and R-squared (R^2) for assessing goodness of fit. These metrics provide valuable insights into the accuracy and precision of the models, guiding further refinement and optimization efforts to enhance predictive capabilities. Given the excellent performance indicated by a low MAPE, we would consider using this model for operational planning, resource allocation, or decision-making related to energy demand. As noted, before, utilizing historical weather data to predict was an essential portion of the model's overall performance. We would want to continually monitor by introducing new data and across different scenarios to ensure its continued accuracy. Overall, achieving an MAPE of 0.75% is a notable achievement and suggests that the linear regression model is well-suited for predicting daily total energy demand. Linear models are commonly used in the analysis of electricity demand due to their simplicity and interpretability. This section describes the linear modeling approach applied to the ERCOT data.

4.2 Time Series Modeling

Where linear models tend to fall short, time series models have more nuances in capturing the temporal dependencies and patterns that we expect to see in time-based data, specifically electricity demand data. We focused the data on just our date range and our predictor variable *Demand*. We leveraged the historical demand data with an ARIMA model to best predict our total energy demand. In the initial phase of our analysis, we prepared a visualization of the original time series data, offering a clear depiction of past demand dynamics. Subsequently when we employed the auto ARIMIA algorithm to identify the optional order for the modeling derived the best order, (2,1,2) to serve as the cornerstone for our modeling efforts. This order signifies the inclusion of two lag observations in the autoregressive (AR) component, a first-order differencing step to achieve stationarity, and a moving average (MA) component with a window size of two. Understanding these components is crucial as they influence how the model captures past observations and errors to generate accurate forecasts.



ARIMA Formula: $y(t) = 2767966454.4254065 + 0.5787894824612647 * y(t-1) + -0.12162907056956529 * y(t-2) + -0.4426505290340541 * e(t-1) + -0.354473478735247 * e(t-2) + e(t)$

Fig. 4 The figure highlights the tail end of the training data while displaying the generated ARIMA Formula used in the model to test data set. The training data is displayed in black and the testing data in gray. The forecasts for different time horizons (7 days, 1 month, 3 months, 6 months, 12 months, and 24 months) are plotted using dashed lines in dark gray. Confidence intervals are shaded around each forecasted value showing the range of values to be predicted against. The 24-month forecast is the most easily recognizable in the figure above.

With an ARIMA model calibrated, we set to forecast daily total energy demand for several different time horizons: 7 days out to 2 years into the future. These forecasts shed light on the anticipated trajectory of energy consumption. This enables stakeholders to proactively plan and allocate resources in alignment with projected demand fluctuations. This allows us to best predict our total energy demand. *Table 4* shows the results of our evaluated forecast accuracy using established metrics including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for assessing goodness of fit.

Table 4. The Models Scores are available between the various ARIMA horizon forecasts tested to predict total energy demand utilizing an 80/20 train test split dataset. We are only highlighting the first 4 different horizons utilized from our forecasts.

Time Series Model Evaluation				
	7-Day Fore- cast	1-Month Forecast	3-Month Forecast	6-Month Forecast

Mean Absolute Error	88,063.81	105,382.57	90,290.77	109,420.85
Root Mean Squared Error	106,253.18	116,262.38	102782.62	126,781.51

We looked at how accurate our predictions were for different time periods: 7 days, 1 month, 3 months, and 6 months. For the 7-day prediction, we found that, on average, we were off by about 88,063 Mega-Watt Hours. During the 1-month prediction, we found that, on average, we were off by about 105,382 Mega-Watt Hours. Similarly, for the 3-month prediction, our average error was around 90,291 Mega-Watt Hours. And for the 6-month prediction, our average error was approximately 109,421 Mega-Watt Hours. These numbers help us understand how close our predictions are to the actual energy demand. Despite some variance in our models, our predictions exhibit commendable accuracy, indicated by the relatively low forecast errors, ongoing refinement and validation efforts remain critical for enhancing predictive capabilities and ensuring robust decision support mechanisms which helps us plan energy needs of the grid better.

5 Discussion

The discussion section of this paper delves into the findings and implications of the modeling methods used to predict total energy demand across the ERCOT grid. Total energy demand modeling is crucial for grid management, resource allocation, and policy development. As highlighted in the literature review, accurate and reliable models of energy demand are essential for informing decision-making processes and optimizing energy infrastructure and resource allocation. This study focused on analyzing methodologies for modeling energy demand, specifically within the context of data sourced from the Electric Reliability Council of Texas (ERCOT) spanning the years 2007 through 2022. The ERCOT dataset offers valuable insights into the diverse and dynamic factors influencing electricity consumption, making it an ideal source for exploring different modeling approaches.

Acknowledging the complexities inherent in energy demand modeling, it is imperative we recognize the significance of weather forecasting in refining predictive accuracy. Weather patterns exert a profound influence on energy consumption, affecting heating and cooling needs, outdoor activities, and overall demand dynamics. However, the inherent uncertainty and variability in weather forecasts introduce limitations to the precision of energy demand predictions. Despite advancements in modeling methodologies, the challenge of imperfect weather knowledge persists, necessitating a nuanced approach to account for its impact. Integrating weather forecasting models into energy demand prediction frameworks enhances predictive capabilities by leveraging historical data and future weather projections. By incorporating anticipated weather conditions, analysts can better capture the dynamic interplay between weather patterns and energy consumption, thereby improving the robustness and reliability of energy demand forecasts. Embracing the inherent uncertainties of weather forecasts while leveraging them as valuable inputs in modeling

endeavors is crucial for advancing the accuracy and effectiveness of energy demand prediction systems within the ERCOT grid and beyond.

Beyond weather conditions, exploring other influences of additional external factors on energy demand, such as economic conditions, technological advancements, and policy changes would be additional areas of consideration to explore. These factors interact with energy consumption patterns in complex ways, shaping demand dynamics and influencing the accuracy of predictive models. By incorporating a broader range of external variables into modeling frameworks, we can improve the robustness and reliability of energy demand forecasts, enabling more effective grid management and resource allocation.

Two major modeling paradigms were considered: Linear Modeling and Time Series Models. Each approach offers unique advantages and limitations in capturing the nuanced behavior of energy demand data. Linear models, as discussed in the literature, are widely employed for their interpretability and computational efficiency but may struggle to capture complex non-linear patterns. Time series models, such as the ARIMA model, excel at capturing temporal dependencies and trends but may require careful parameter tuning and struggle with extreme events or unforeseen external factors. Addressing the uncertainty associated with energy demand forecasts is essential for effective decision-making. While linear and time series models were the primary focus of the study, exploring alternative modeling approaches could potentially offer additional insights into energy demand prediction. Machine learning techniques such as neural networks or ensemble techniques may be better suited to capture complex relationships and non-linear patterns within the data. By evaluating a broader range of modeling approaches, researchers can identify the most suitable techniques for specific forecasting tasks and improve overall prediction accuracy, contributing to more robust energy demand forecasting systems. While this study provides insights into model performance metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), a more in-depth discussion of uncertainty quantification techniques could enrich the analysis performed. Methods such as probabilistic forecasting or ensemble modeling could further assess and communicate the range of possible outcomes, enabling stakeholders to better manage risks and plan for contingencies in energy supply and demand.

Data preprocessing, as emphasized in the literature review, plays a crucial role in preparing the dataset for analysis. The team employed a meticulous process of cleaning and standardizing the data, including transposing the data into a more conducive format, standardizing date formats, and joining weather data from different regions within the ERCOT network. This process ensures that the dataset is clean and enriched, ready for in-depth analysis and modeling. We wanted to expand the dimensionality of our models by integrating a weather forecasting model to be able to combine historical and future weather pattern predictions to see how that might influence our prediction algorithms.

Our results proved very promising in predicting and forecasting daily energy demand as highlighted in the results section, having evaluated the performance of linear and time series modeling approaches in predicting energy demand across the ERCOT grid. Overall, the discussion underscores the importance of continued research and innovation in modeling techniques to address the evolving challenges of the energy sector and ensure the sustainability and reliability of energy systems within the ERCOT system.

Ethically, this study and its datasets do not directly involve social issues or data on people. The ethical considerations in the analysis or data collection are not as clear, however, these issues were not a central theme of this paper as they may be in a people-oriented field of study. That being the case, considerations for linking modeling results to broader policy objectives and sustainability initiatives are critical for translating research findings into real-world impact. Leveraging such results can inform decisions on renewable energy integration, carbon emissions reduction, and other infrastructure investments. By aligning modeling efforts with overarching policy goals, stakeholders can work towards building more resilient and sustainable energy systems that meet the needs of society and the environment, contributing to long-term energy security and environmental sustainability.

Engaging with diverse stakeholder perspectives is essential for ensuring the relevance and applicability of energy demand modeling efforts. By involving policymakers, industry professionals, researchers, and the public in the discussion, we can gain valuable insights into the practical challenges and opportunities associated with demand forecasting. Incorporating stakeholder feedback into modeling frameworks can enhance their usability and effectiveness in addressing real-world energy challenges that we see every day. Fostering collaboration and collective action towards a more sustainable energy future we can take great strides toward protecting ourselves and our world in the most efficient and effective ways possible. However, knowing the situation is only the first of many steps, we must ensure as accurate information as possible. Practically, this involves making relevant data publicly available whenever possible. It is imperative not to protect business interests or give to unfair impassioned objections. The integrity of the data and its collection and that of our analyses must reflect the gravity of our situation to our best abilities. The writers of this study have conducted this research with the intent to respect the importance of this issue within the constraints of their resources, and hope that further research done with relevance to, or citation of this study is done in similar spirits.

6 Conclusion

As society pushes forward towards sustainable energy there are many challenges that have yet to be overcome. Among these challenges is the ability to forecast the demand for power. It is imperative to ensure that there is enough generation to keep up with the ever-growing demand. ERCOT has struggled in recent years through extreme weather events and the high summer temperatures in Texas, as such models that forecast power demand can be of the utmost utility. These struggles were what brought this issue to the researcher's attention.

The research done in this paper and the models created achieved commendable accuracy. The models successfully forecasted power demand over the next decade but also could be used in a more operational sense where they could be adapted to forecast a shorter period such as the upcoming weeks or months. This operational application is particularly valuable for identifying potential deficits in power supply, enabling proactive measures such as utilizing stored energy in batteries to mitigate shortfalls.

Moreover, the researchers envisage these models as a springboard for further exploration and innovation in energy demand forecasting. We advocate for the integration of

weather forecasting models into the power demand forecasting framework to enhance predictive accuracy and reliability to meet current energy demand. By combining historical energy demand data with future weather projections, researchers can gain deeper insights into the complex interactions between weather patterns and energy consumption. These efforts will further refine predictive models and bolster the resilience of future energy systems. The models developed in this study offer both immediate operational benefits and long-term potential for further refinement and innovation. By leveraging these models in conjunction with innovative forecasting techniques, stakeholders can achieve a more sustainable and resilient energy future.

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