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Modeling Electric Energy Generation in ERCOT during Extreme Weather Events and the Impact Renewable Energy has on Grid Reliability

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1 Introduction

The Electric Reliability Council of Texas (ERCOT) is an Independent System Operator (ISO), the central electricity operator in Texas. ERCOT is not connected to any other grid in North America. As an ISO, it is solely responsible for running the electric grid for most of Texas, planning for reliability, and providing wholesale rates for electricity. In February 2021, Texas experienced extremely frigid temperatures causing large blackouts throughout ERCOTs service area, leading to the loss of hundreds of lives and billions of dollars in economic damages.

Part of reliability planning is demand response. The grid reduces power generation during normal declines in electric load. During peak periods, the generators connected to the grid produce more power. This mechanism catastrophically failed during the recent blackouts.

This paper aims to provide insights on ERCOT demand response during peak electric consumption. As ERCOTs service area population continues to increase and the weather impacts consumption and the generation of power in Texas, it is beneficial to understand the changes necessary to ensure a reliable electric grid. As demand increases, supply must also increase to meet that demand. Generation supply and electrical demand are mirror images of each other. ERCOT does not import or export power to any great extent. Power storage is in its' infancy and not a significant contributor. Therefore, demand and supply balance each other out, and any changes in one affect the other. This paper will analyze ERCOT outages to understand ERCOTs demand response and the changes that need to be made to accommodate the increase in electricity consumption. The blackouts in Texas this past February had several causes. This paper will show that increased reliance on renewables and inadequate backup generation was a primary cause of the blackouts.

Additionally, increased reliance on renewables poses other risks to reliable grid operation that can manifest themselves under more normal operating regimes. The paper explores the characteristics of traditional generation sources and how they benefit grid reliability. Also examined are the issues created by renewable energy forming a significant part of the electric generation on the grid and how this form of generation lacks normal grid stabilizing characteristics.

Demand response in extreme weather circumstances is not a well-understood phenomenon due to a lack of examples. Of particular concern is the absence of historical data that includes the current prevalence of renewable energy on the electric grid. Under almost all circumstances, electric demand follows classic time-series patterns. The paper proposes time-series models that include the necessary parameters to satisfy extreme operating conditions.

Extreme operating conditions are only some of the issues relating to grid reliability. The electric grid requires reserve power to deal with generation or transmission outages and other technical problems even under normal operating conditions. As the percentage of renewable energy increases, certain negative consequences occur that traditional power generation sources would normally mitigate. This paper uses modeling to answer what portion of electric generation can be met from renewable sources before impacting grid reliability.

It is not only the maximum peak load that can present problems. Unexpected load that deviates from the norm and occurs out of season can create issues as well. From a generation standpoint, extremely light load conditions can be problematic as they can concentrate the amount of renewable power on the grid, impairing grid reliability.

Enhancing grid reliability is important to every person in ERCOTs service area. The recent blackouts demonstrate the severe negative consequences of unreliable electric power. However, it is not just during severe weather events that reliable power is important. Reliable electric power is necessary for normal life and commerce (Edison Electric Institute, 2020). Blackouts can have numerous negative financial consequences and potentially life-threatening ones.

2 Literature Review

2.1 How the electric grid works

When researching electric power an issue that repeatedly crops up in reviewing the literature, whether done intentionally, the terms “Watt” (W) and “Watt-hour” (Wh) and their derivatives are frequently confused. This is seen in literature and announcements of new projects and technologies such as batteries. A Watt is a rate at which power can be delivered. Watts are directly related to the concept of horsepower; 746 Watts equals one horsepower. Watt-hour is the total amount of energy produced or consumed. Using an automobile as an analogy Watts are how much power that can be delivered by the engine at a given moment, Watt-hours represent the total energy content of the fuel in the fuel tank.

The electric grid has three main components generation, transmission, and load. Generation consists of a limited number of power plants, each with one or more generating units. All generating units at a power plant typically run on the same type of fuel. Thus, it is common to refer to the plant as a gas plant or coal plant in the industry.

Texas's electric power transmission system moves electricity generated in one part of the state to the load centers in other parts of the state. Particular generation units are only available in one part of the state. Wind generation is primarily located in the panhandle region of Texas. Lignite coal generation units are typically located with direct access to the fuel source due to the low energy density of the coal and the high cost of moving it. Also, problems in one area of the state can be met by transmitting power from another part of the state if necessary. The backbone of the Texas transmission grid is formed from multiple 345kV transmission lines. These lines move electric power around the state.

"Load" is any consumer of electric power. The load can vary from individual homes in a suburb consuming 20 kW of power with 1500 kWh of total electric consumption per month to an aluminum smelter pot line consuming 500 mW of power with a total monthly consumption of 360 gWh. The largest load center is typically cities.

All generation units in Texas, and the rest of the U.S., generate power at a frequency of 60 Hz. This corresponds to 3600 revolutions per minute. All generation units on the electric grid are in phase and spinning at the same rate. The term "in phase" means that the peak of the sinusoidal waveform matches that of all other generation units. Generation units pulling out of phase carries the potential of causing damage to the units and requires shutdowns and inspections (Ruthford, 2021). Electric generation units have two main controls that affect the power delivered. The first is a load/speed governor. When a unit is unconnected to the grid, this control will determine how fast the generating unit turns. The load/speed governor determines how much power the generating unit produces when connected to the grid. The second control is voltage control. All generating units generate power at a rated voltage. When the generating unit is not tied to the grid, the voltage control sets the amount of voltage on the generator's output, typically expressed in units of kilovolts (kV). When tied to the grid, the voltage control affects the reactive power output of the generating unit. Reactive power issues will be discussed later in this paper.

2.2 Grid Stabilizing Influences of Renewable and Traditional Power Sources

The momentum of rotating turbines and generators plays an integral part in grid reliability. The large rotating masses present in traditional generating sources store potential energy. This potential energy is available to the grid because these generating sources are directly tied to the grid. The potential energy present in the inertia of the rotating equipment dampens transient power fluctuations on the grid. Solar power has no rotating store of potential energy and wind power has relatively little. Also, renewables connect to the grid through inverters. Without a direct connection to the grid, renewables cannot be used to stabilize the grid from power fluctuations (Fanglei et al., 2020, p. 607). All generators on a grid spin at the same speed and are in phase. Under normal operation generation unit trips are compensated for instantly by trading inertia for power. The grid frequency slows down, some of the rotating inertia is converted to additional power. The output of the remaining units is ramped up with the extra load, and additional units placed online as necessary. Wind and solar power rely on inverters to couple to the grid. "Renewable energy sources with low inertia generators are posing serious operational and analytical issues in power systems" (Lin & Varwandkar, 2019, p. 1). Neither renewable source can compensate for generation unit trips or other system issues by training rotational inertia for power.

Trading momentum for power does have limits. AC power equipment is rated for specific voltages at specific frequencies. The ratio between voltage and frequency is critical. For example, a generator rated at 13.8kV at 60 Hz is rated at only 11.5kV at 50Hz. This relationship between Volts and Hertz limits the ability of the grid to rely on momentum to continue to supply power. The slower speeds eventually result in generation units tripping or automatically reducing voltage. "If the Texas grid stays below 59.4Hz for nine minutes, generators would have automatically tripped out, making a bad situation for people shivering at home even worse” (Burton, 2021).

While not commonly understood, AC electric power demand is composed of two parts. Most people are familiar with the concept of power; not many people are familiar with reactive power. Loads on a grid are composed of resistive and either a capacitive or inductive load component. The resistive load component quantifies the real work that electricity does. However, the inductive or capacitive load also referred to as reactive power, is a real quantity intrinsic to a given load. Inductive loads are typically found in anything with a coil of wire wrapped around an iron core, such as motors or transformers. Capacitive loads are less common on the grid, but a typical case would be lightly loaded transmission lines, long parallel conductors forming a capacitor. Failure to supply the correct reactive load leads to voltage problems. Too much excess inductive load leads to lower line voltages and an increase in current. As current increases, the efficiency of equipment connected to the grid decreases, leading to reduced transmission and distribution equipment capacity. Exceeding the required capacitive load can cause excessive voltage on equipment and lead to sections of the grid slipping out of phase and causing blackouts and damage to equipment. The phase lock of the grid becomes weak when capacitive loads dominate the grid. Losing the phase lock, called slipping a pole, on a generating unit or a grid section causes enormous problems, often resulting in protective relays tripping units and extended outage times spent inspecting and repairing equipment. Generation equipment must supply the correct output for both power and reactive load on the grid as a whole and locally. The current push to renewables presents new challenges.

Power from REG’s, renewable energy generation, is variable and intermittent. When REG sources comprise a significant portion of the grid, their shortcomings affect the available power on the grid and create voltage issues. The grid voltage is directly related to reactive power supplies. Also, amplifying the issue in the case of Texas, the REG’s are located at a considerable distance from the load centers. These long-distance spans with unreliable voltage support can amplify the negative effects on grid reliability (Sarkar et al., 2018, p. 41460).

Inverter based resources (IBR), including wind and solar, are also intrinsically vulnerable to grid frequency and voltage disturbances. IBR’s lack the stabilizing influence of potential energy contained in the mass of rotating equipment. The electronics of the inverters themselves are vulnerable to system transients, whether frequency or voltage. California had instances in 2016 and 2017 during which the REG’s disconnected from the grid because they could not tolerate grid instabilities (Romero Aguero et al., 2019, p. 78).

2.3 Time of use Considerations for Energy Consumption

The widespread adoption of renewables in ERCOT and other areas causes unique challenges to grid reliability. REG’s are not dispatchable in the traditional sense; the generators create as much power as they can when they can. This is often dictated by law and policy. Various pricing schemes have been tried to alleviate both production and demand issues. Demand issues affect grids even if no renewable generation is present. Wind energy in ERCOT is available in the Texas panhandle, which is very far removed from the areas with the largest demand. This creates a need for extra capacity on the electric grid and attenuates the generated power. The California Independent System Operator (CAISO) currently experiences steep demand increases daily, starting at about the same time available solar power begins to wane (Romero Aguero et al., 2019, p. 77).

Demand response, otherwise known as DR, is a key means of controlling electrical demand. “The best candidates for DR are commercial/industrial customers” (Romero Aguero et al., 2019, p. 80). Power curtailment agreements with larger customers are standard in ERCOT’s operating region; indeed, SMU has such an agreement.

Time of use (TOU) pricing structures has also been used to reduce demand during peak load events. TOU pricing requires advanced metering infrastructure (AMI). Traditional electric meters just record how much power is used. The newer AMI systems allow variable pricing depending upon the time of day. During 2012 due to a lack of AMI 98% of utility customers in the U.S. were charged a flat rate for electricity. By 2014 50 million advanced meters had been installed. This covers almost half the homes in the country (Zhao et al., 2017, p. 5130). The prevalence of advanced meters now allows for alternative variable pricing programs to become more common. This would be a significant shift in practice for U.S. customers (Cappers et al., 2016, p. 16).

2.4 Modeling the Electric Grid

The electric grid generation demand can be modeled as a time-series. Parameters and additional data are used as necessary. Parameters are adjusted to try and match the statistical characteristics of previously modeled days. The parameters can be days of the week, general weather conditions, the prevalence of REG power on the grid (Hong Li et al., 2015, p. 2). Forecasting short-term-load demands requires consideration of time-series and other characteristics. Short-term load forecasting has periodic and regular characteristics. Factors such as temperature, weather, and economic activity can affect the demand forecast (Hong Li et al., 2015, p. 2). In Texas, expected wind speed in the panhandle area is critical in predicting REG availability.

The periodicity of the load is significant in forecasting demand. The more regular the daily load cycle is, the greater the possible accuracy of the models. The accuracy of the models becomes dependent upon external factors like weather (Hong Li et al., 2015, p. 1).

Electric demand modeling requires different models for different periods. Days will need to be classified by their expected load characteristics. For instance, weekends and weekdays will exhibit different demand curves. In one instance, when examining the demand of a university, the different types of days were broken down by academic period and day of the week resulting in improved models (Garcia et al., 2018, p. 1).

Short-term forecasting is key to grid stability (He et al., 2012, p. 297). It is possible to estimate demand using an ARIMA model. “The accuracies of the models are very impressive as the MAPEs(Mean Absolute Prediction Errors) are approximate 1.5%. As we can gather the real-time data from AMI system of the distribution power grid, a single seasonal ARIMA model can be used to forecast the next day’s load demand very accurately” (He et al., 2012, p. 297). One advantage is that grid reliability can be achieved with only the near-term, next several hours, forecasts. Accurate longer-term forecasts are still important as they reduce costs by enabling prior dispatching of generation resources. Direct comparison between grid conditions in China and ERCOT is not always possible. China's grid changes rapidly, and the previously mentioned paper only uses recent data. The conditions of the electric grid on both the demand and generation side change rapidly in China. This leads to an emphasis on short-term forecasting (He et al., 2012, p. 297).

2.5 Spinning Reserve

A key measure used for electric grid reliability is the concept of spinning reserve. Spinning reserve refers to the amount of power that is potentially available on the grid from generation units with extra or peak capacity. Normally generation units are run at full load. However, most have a peak capability as well. Peak generation is when generation units produce beyond their rated capacity for short periods (Porkar et al., 2006, p. 1341). Usually, the spinning reserve is set at some percentage of expected demand on the grid. A useful outcome of the models in this paper will be modifications to the spinning reserve requirement based upon more than just the total demand.
Time-series can be used to forecast grid demand. However, the high prevalence of renewables presents unique challenges to grid reliability and modeling. Newer technologies such as smart grids and large-scale energy storage can help alleviate these challenges. Time-series models can be constructed to forecast expected demand and determine the maximum safe proportion of renewable energy present on the grid at any time given the expected conditions and penetration of smart grid technologies and large-scale energy storage. Time-series forecasts can also be used to modify the required spinning reserve for safe grid operation.

3 Methods

Time-series will form the basis of the analysis used in this research. It will be necessary to classify days into demand clusters. Deviations from the expected demand will be modeled. Different seasons impact the normal distribution of power demand. Weather and specifically temperature greatly influence electric demand. ERCOT generation data and NOAA weather data are the primary data sets used in this paper.

3.1 Time-series

Electric demand follows a classic time-series sinusoidal pattern. However, the average daily consumption of electric power deviates from a simple time-series for several reasons. When examined on a year-over-year basis electric demand follows the classic airline model. Airline models are defined as "a model that allows for seasonal and trending behavior" (Woodward et al., 2017, p. 344). Historically the electric power industry assumes electric demand will grow at double GDP growth (Ruthford, 2021). This provides a positive trend for the highly seasonal power demand data.

Power demand has different seasonal periods. Power demand displays a pronounced hourly trend when measured over a day. Also, daily demand curves are different depending upon which day of the week and whether the day is a holiday. Finally, power demand varies by season. Not only does the average daily demand change, but the demand curve within the day also changes characteristics.

3.2 Seasonality and Time Series

The time-series models used will need to account for all these different seasonality factors. The model created will use one hot encoded variables for month of year, day of week, and hour of day. This model also uses temperature data since it is a major driver of electric power usage.

3.3 Demand and ERCOT data

Generation data is collected from ERCOT. The data files are in fifteen-minute intervals, and the power amounts are broken down by fuel type. The data is remarkably complete and requires little cleaning. However, the format of the data is not convenient for processing. The data is normalized by aggregating the fifteen-minute intervals into an hourly format.

Having data that separates the different generation sources allows closer inspection of the amount of power that is provided from different sources and when that power is available. The total power generated follows a sinusoidal pattern, the individual sources are much more chaotic in producing power.

Power Data EDA

Three years of data 2017 to 2019 were used as training data. A single year of data 2020 was used for testing. The ERCOT power data is strongly cyclic. Under normal circumstances it follows a uniform behavior. February of 2021 was a departure from this normal behavior. Power generation with normal and extreme weather is shown in the graphs below. Both graphs are from February of their respective years. The graphs show different generation patterns, with the key difference being the extreme cold weather in February of 2021.

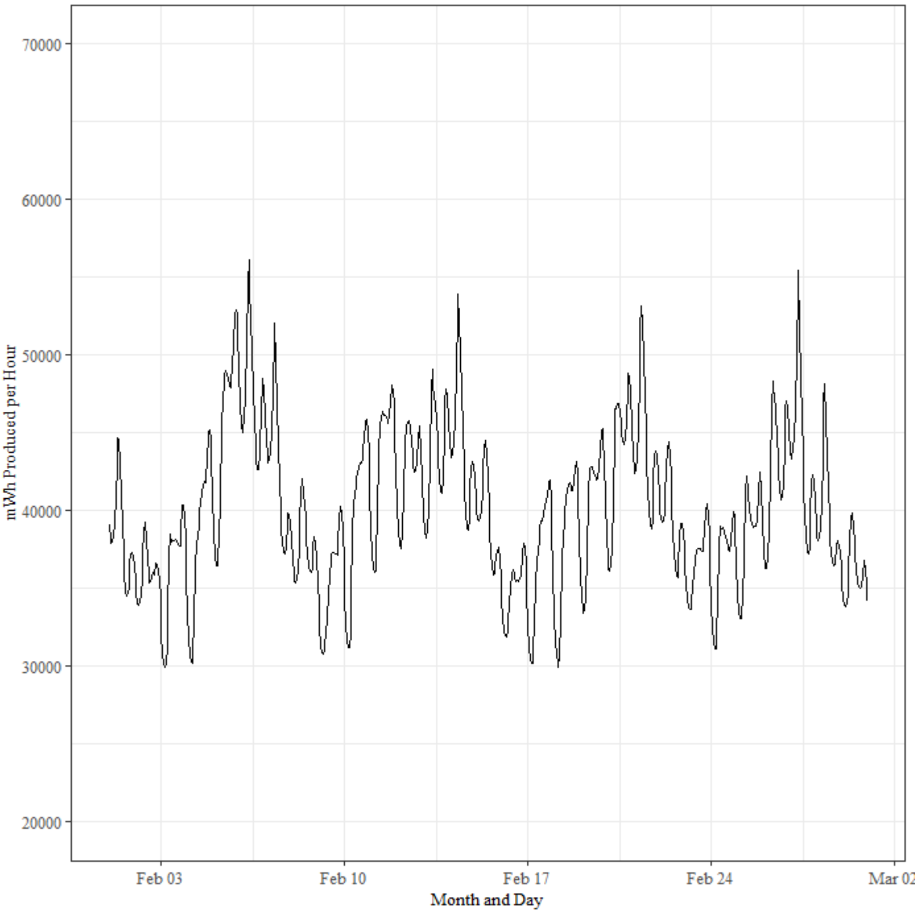

Fig. 1. The total power produced in ERCOT by the hour for February 2020. Data demonstrates strong cyclic behavior with the highest and lowest generation spread across the entire month.

The data in Figure 1 shows typical power production. Some variances in the basic cyclic pattern can be observed. A variety of factors influences these variances. Models using these factors are necessary to explain the differences observed. This becomes incredibly important when looking at the data gathered during the extreme cold weather event in February of 2021. The data gathered does not tell the whole story. If power was not produced, even if demand was there, it can not be measured. Looking at only the data collected does not indicate how much power was needed. Establishing models that can be used to extrapolate the true power demand are needed to plan additional generation units for the grid.

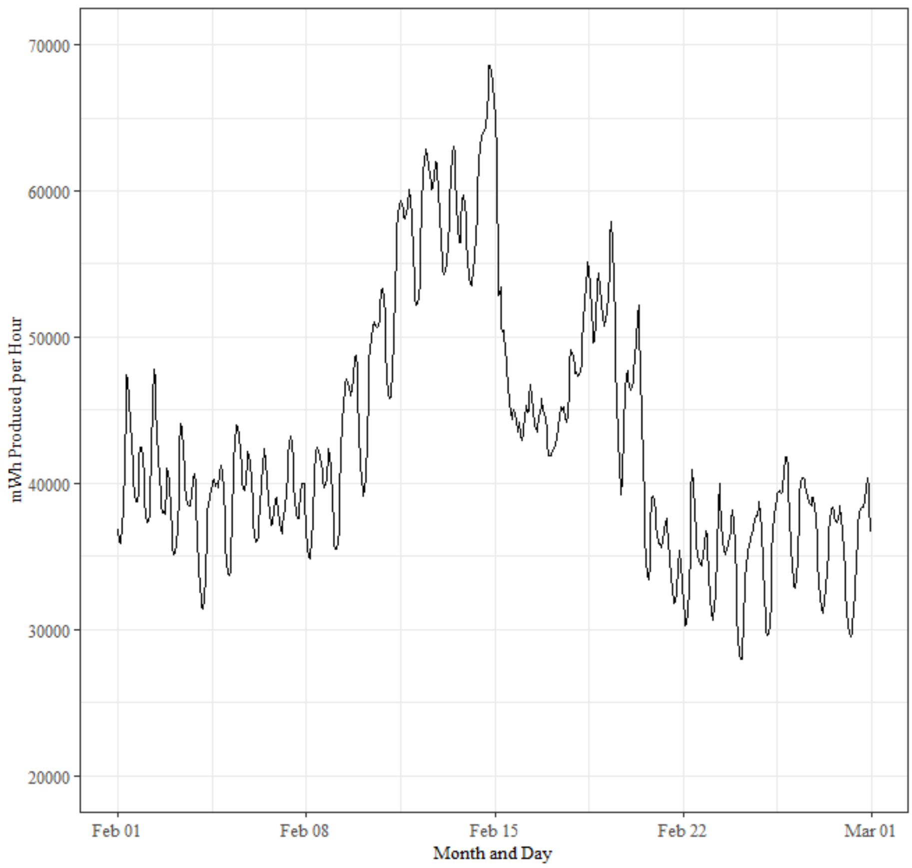

Fig. 2. The total power produced in ERCOT by the hour for February 2021. Data demonstrates cyclic behavior except during the time of the blackouts. The blackouts are characterized by a large peak in the middle of the month followed by a steep trough.

Figure 2 shows a substantial generation peak in the middle of the month followed by a steep drop-off starting on the 15th. This corresponds with the beginning of the forced outages. Notice that during the trough, the normal cyclic behavior of power generation is muted. All generation that was able to run was producing power during that time. The normal cyclic behavior instead was handled by load shedding, more customers disconnected during times of high demand since no power was available. Modeling the expected power demand during this event is a key factor in improving grid reliability. The exact load numbers required at that time can not be determined from either generation or demand data. There is no way to measure it.

Compounding the task is the use of renewable energy. At one point during the extreme weather, renewables were only able to provide 634 mWh per hour. This contrasts with renewables providing a mean value of almost 11,000 mWh per hour during February of 2020. Grid reliability depends upon having dispatchable power ready right now.

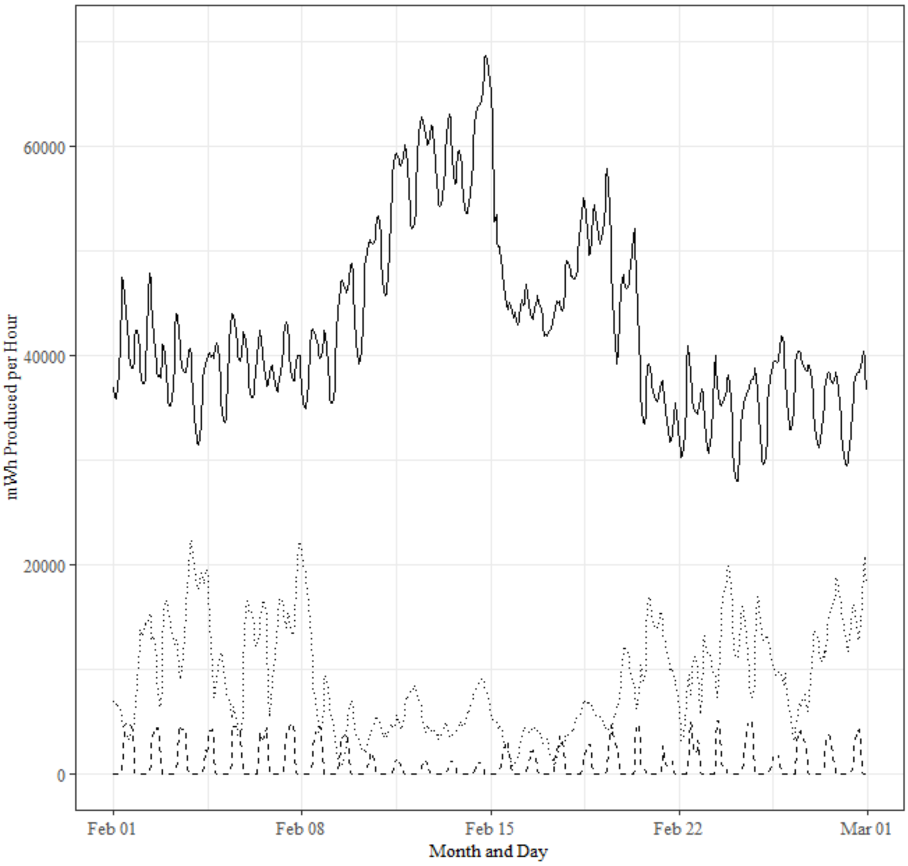

Fig. 3. The total power produced in ERCOT by the hour for February 2021 includes wind power (*dotted line*) and solar power(*dashed line*).

Figure 3 shows the almost nonexistent power produced by renewables when the grid was at its point of greatest distress. During the first and last weeks of the month, more normal conditions prevailed. During these times, renewables routinely comprised 50% of electric generation.

Figure 1 through 3, examined power production on a monthly time frame with an hourly time scale. The daily cyclic behavior of power generation is self-evident.

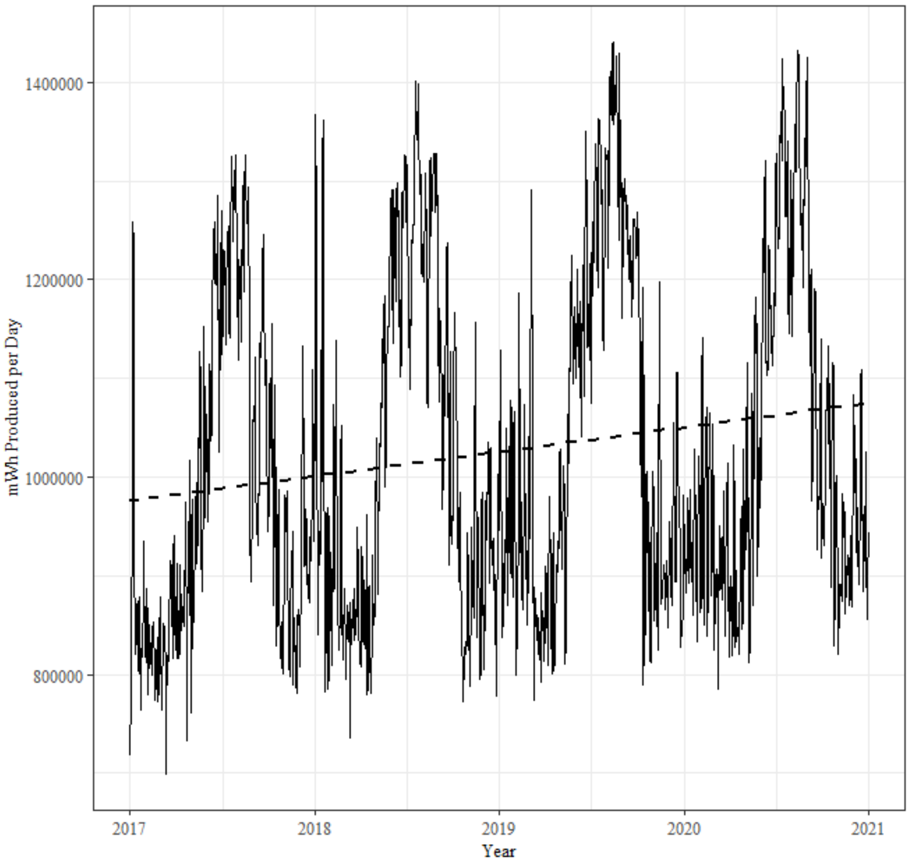

Fig. 4. This figure indicates the daily power production in mWh in ERCOT for the years 2017 to 2020 inclusive. The daily power production line shows cyclic behavior with some variances. The (*dashed line*) is a linear fit of the data with respect to time. The line shows a steady increase.

The normal assumption with power generation data is that it follows the classic airline model. Figure 4 shows the daily production of power over the previous four years. Included on the graph is a linear fit of the data. This linear fit clearly demonstrates a rise over time. The figure clearly shows seasonal variations. These behaviors match the expectations if power data follows an airline model.

3.4 Weather and NOAA data

Weather is a contributing factor to electric demand and is critical to modeling demand accurately. Temperature plays a primary role in determining demand. Wind and cloud cover determine the availability of renewable power. Humidity and temperature have an impact on the availability of traditional power sources.

This paper uses data from the NOAA website as a primary resource. The NOAA website provides hourly data from different stations. Sometimes the data is more frequent. Stations can be located anywhere, but a common location is local airports. Many of the smaller stations display anomalies in the data. This typically takes the form of missing data. Missing weather data was imputed using the MICE library. MICE works by fitting multiple linear models to all data present and building linear models that describe each vector of data, a vector of data being the values of a variable over time.

Weather Data EDA

Fourteen geographically diverse weather sites were examined so that the resulting models can utilize different parameters. A single weather station for the entire state would not be representative of the weather and would lead to overly simplistic models. Three years of data from 2017 to 2019 were used as training data. A single year of data 2020 was used for testing.

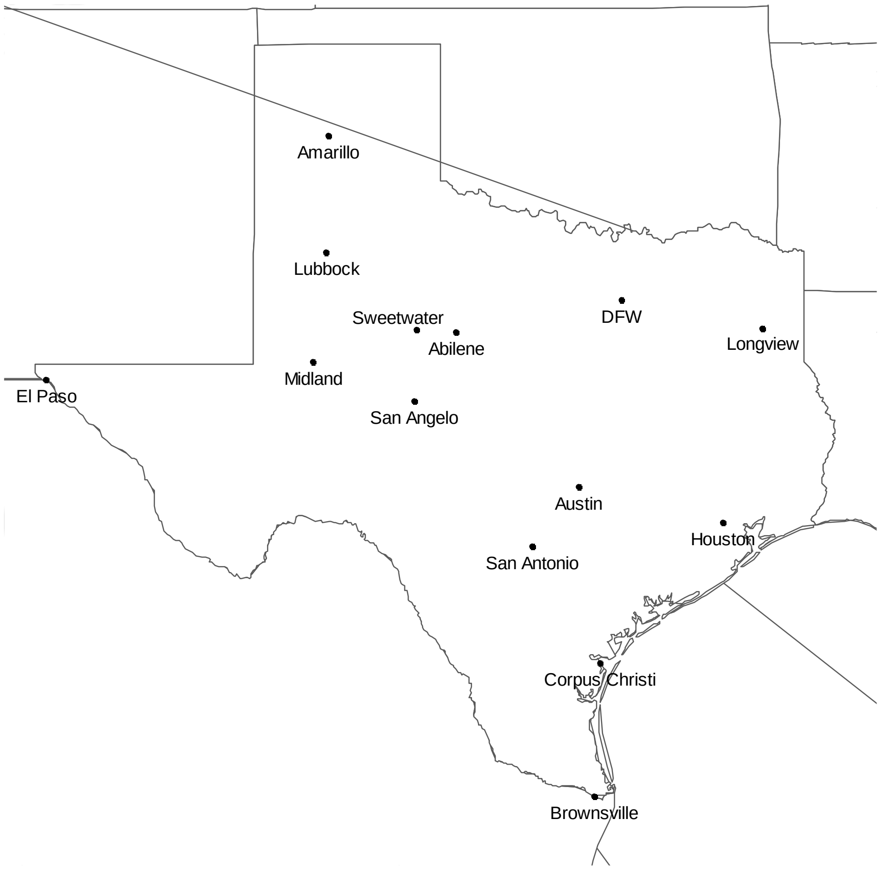

Fig. 5. Map of the fourteen weather stations used for this paper

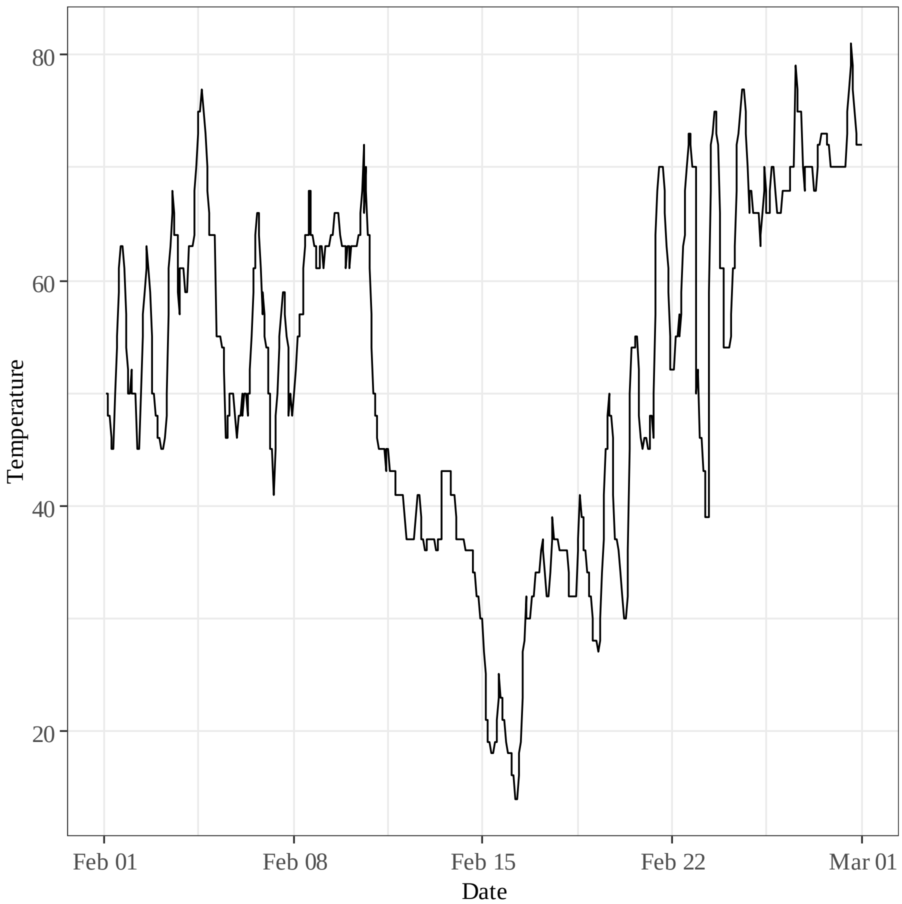

Fig. 6. Hourly temperature data for Houston, Texas recorded in February 2021. Data includes temperature at the time of the extreme cold spell.

The data in Figure 6 does have some missing data. These are identified as straight horizontal lines in the temperature data. However, some NOAA weather stations have much greater issues with missing data.

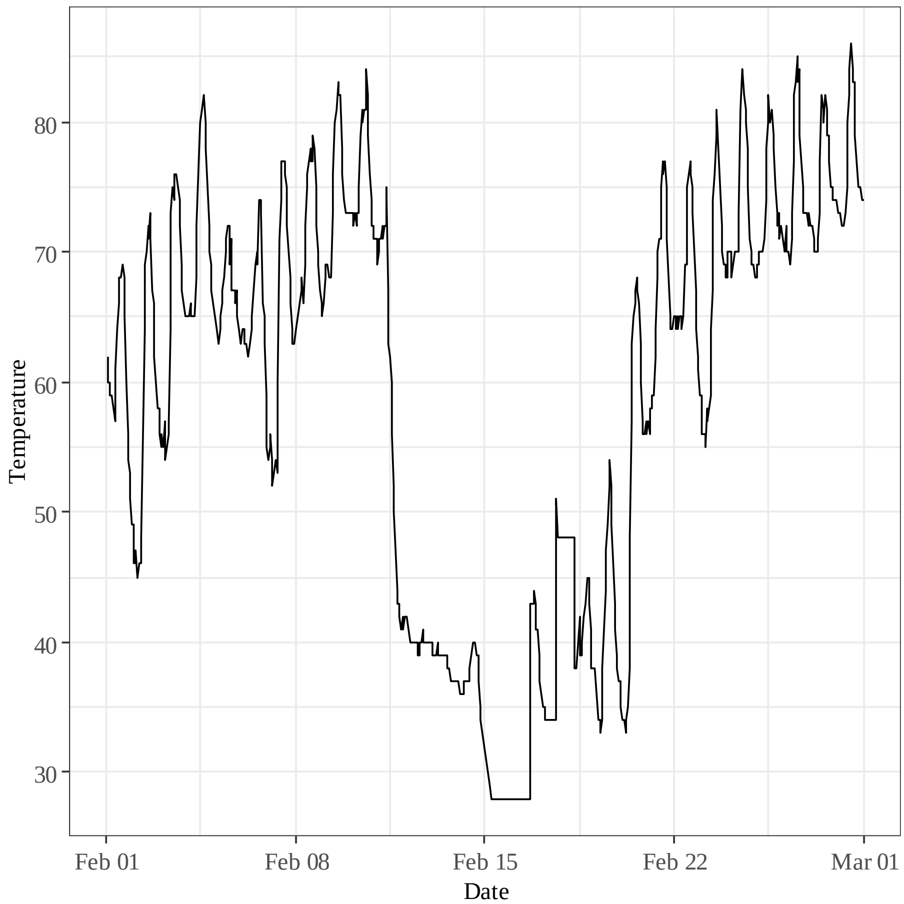

Fig. 7. Hourly temperature data for Brownsville, Texas recorded in February 2021. Data includes temperature at the time of the extreme cold spell.

The Brownsville data in Figure 7 shows several sections of horizontal flat lines indicating missing data. The source data for this station was corrected before using.

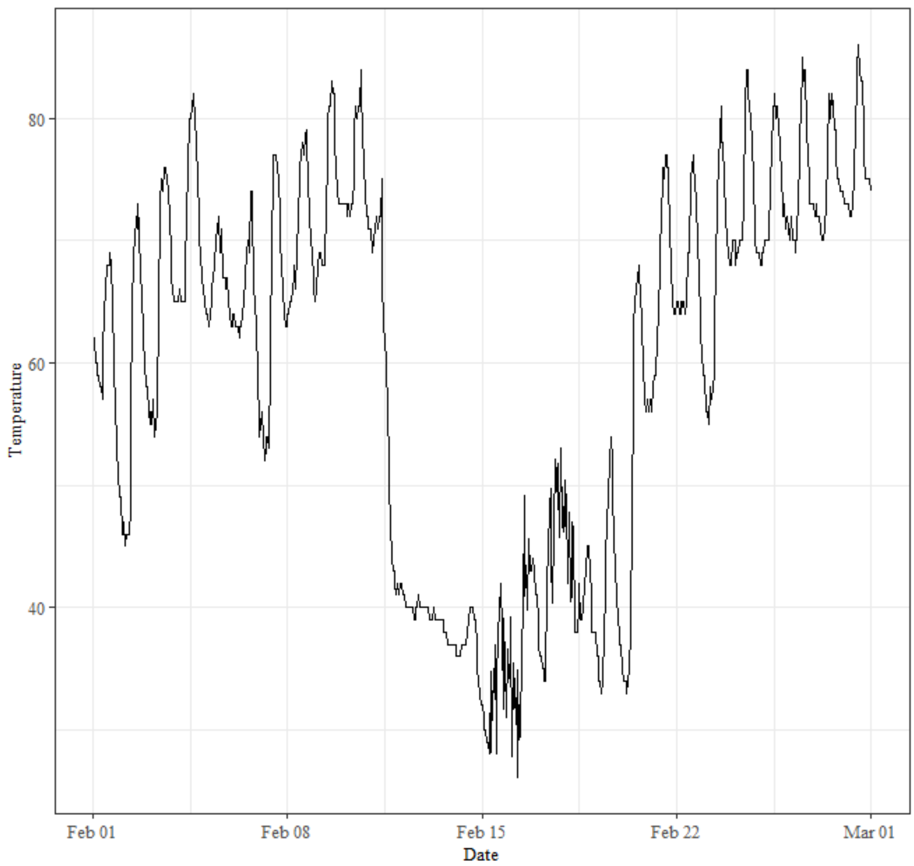

Fig. 8. Hourly temperature data for Brownsville, Texas recorded in February 2021. Data includes temperature at the time of the extreme cold spell. Missing data was imputed with MICE

Missing values in the weather data were imputed using MICE. The Brownsville data in Figure 8 shows the result of this imputation.

Heating and cooling represent the bulk of the difference in demand for electricity. At temperatures in the low to mid-70s electric demand is at a minimum. It is normal for planned outages on generating units to occur in the spring and fall for this reason (Ruthford, 2021). A temperature score was created for use in modeling. The equation for the score is seen below.

$$TemperatureScore = \begin{matrix} Temperature \geq 72 & Temperature - 72 \\ Temperature < 72 & (72 - Temperature) * 0.6 \end{matrix}$$

Eq. 1. Temperature score equation

The temperature score takes the absolute difference between the current temperature and 72 degrees. If the temperature is lower than 72, a correction factor of 60% is applied. The reason for this is that it is heating a home is more energy-efficient than cooling one. Also, a significant amount of heating is done with natural gas and thus requires no electricity. Adjustments to this temperature score methodology would be one area that further study would be beneficial.

4 Results

Multiplpe Linear Regression with Time Series errors and seasonality

Multiple ARIMA models were fit with different lags, AR(10) model was selected based upon AIC score. AIC is the Akaike's information criteria, and is a common measure for goodness of model fit (S. Prabhat, 2010) These models included temperature score data for regression as well as seasonality factors. However, the arima() function lacks the ability to model multiple seasonal components (Krispin, 2019, p. 274). An examination of residuals for the ARIMA model shows evidence of multiple seasonality factors. The final arima() model fitted took the form:

$$\begin{aligned} PowerOutput = 42537 &+ 45.54T_{Abilene} + 47.72T_{Amarillo} + 53.13T_{Austin} \\ &- 31.44T_{Brownsville} + 36.12T_{CorpusChristi} - 6.15T_{DFW} \\ &+ 22.75T_{ElPaso} + 1.47T_{Houston} + 0.32T_{Longview} + 28.83T_{Lubbock} \\ &+ 71.26T_{Midland} + 84.55T_{SanAngelo} + 38.04T_{SanAntonio} \\ &+ 121.58T_{Sweetwater} \end{aligned}$$

Eq. 2. Equation for the Multiple Linear Regression part of the model

$$\begin{aligned} (1 - B^{24})(1 - 1.79B + 0.834B^2 - 0.037B^3 - 0.028B^4 + 0.086B^5 + 0.023B^6 \\ - 0.037B^7 - 0.006B^8 - 0.0009B^9 - 0.023B^{10})Z_t = 0 \end{aligned}$$

Eq. 3. Equation for the AR part of the model

Parameter	Estimate	Std. Error	z value	Pr(>|z|)	Signifigance
ar1	1.79E+00	6.46E-03	277.3004	< 2.2e-16	***
ar2	-8.34E-01	1.32E-02	-63.3296	< 2.2e-16	***
ar3	3.66E-02	1.38E-02	2.6468	0.008125	**
ar4	2.78E-02	1.37E-02	2.0294	0.042421	*
ar5	-8.60E-02	1.37E-02	-6.2906	3.16E-10	***
ar6	-2.33E-02	1.37E-02	-1.705	0.088186	.
ar7	3.73E-02	1.37E-02	2.7255	0.00642	**
ar8	6.01E-03	1.37E-02	0.4398	0.660103	
ar9	9.34E-04	1.27E-02	0.0738	0.941165	

ar10	**2.25E-02**	**6.17E-03**	**3.6524**	**0.00026**	*******
sma1	**6.06E-01**	**4.35E-03**	**139.413**	**< 2.2e-16**	*******
intercept	**4.25E+04**	**3.07E+02**	**138.4504**	**< 2.2e-16**	*******
TempScaleAbilene	**4.55E+01**	**1.34E+01**	**3.3911**	**0.000696**	*******
TempScaleAmarillo	**4.77E+01**	**1.18E+01**	**4.0324**	**5.52E-05**	*******
TempScaleAustin	**5.31E+01**	**1.15E+01**	**4.6113**	**4.00E-06**	*******
TempScaleBrownsville	**-3.14E+01**	**1.10E+01**	**-2.8505**	**0.004365**	******
TempScaleCorpusChristi	**3.61E+01**	**1.12E+01**	**3.2169**	**0.001296**	******
TempScaleDFW	**-6.15E+00**	**1.34E+01**	**-0.4582**	**0.646778**	
TempScaleElPaso	**2.28E+01**	**1.29E+01**	**1.7681**	**0.077037**	**.**
TempScaleHouston	**1.47E+00**	**1.13E+01**	**0.1308**	**0.895922**	
TempScaleLongview	**3.23E-01**	**1.30E+01**	**0.0248**	**0.980197**	
TempScaleLubbock	**2.88E+01**	**1.11E+01**	**2.5893**	**0.009616**	******
TempScaleMidland	**7.13E+01**	**1.28E+01**	**5.5814**	**2.39E-08**	*******
TempScaleSanAngelo	**8.45E+01**	**1.25E+01**	**6.7457**	**1.52E-11**	*******
TempScaleSanAntonio	**3.80E+01**	**1.26E+01**	**3.0218**	**0.002513**	******
TempScaleSweetwater	**1.22E+02**	**1.75E+01**	**6.9487**	**3.69E-12**	*******

Tbl. 1 Parameters for arima() function model

The temperature coefficients in table 1 show some unexpected values. The temperature in the two largest metropolitan areas, Houston and DFW, appears to not be statistically significant. The model overall has a poor MAPE (Mean Absolute Prediction Error) score of 13.40%.

As George E. P. Box once said “All models are wrong; some models are useful”. This situation applies to the model derived with the arima() function. Even though the predictive power of the model is low, the model residuals are useful because they show the three seasonalities present in the data, see figures 9 through 11

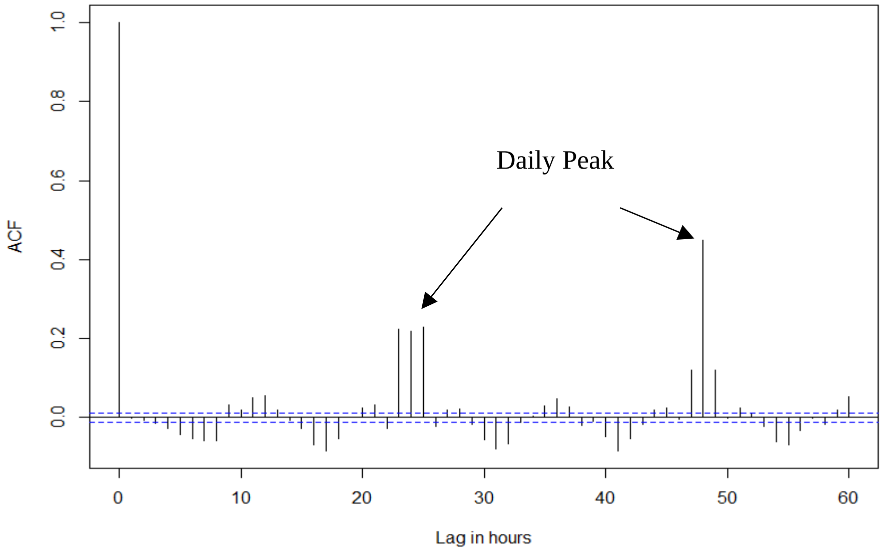

Fig. 9. ACF plot of ARIMA model residuals, 24-hour autocorrelation

Figure 9 shows that a strong autocorrelation still exists in the ARIMA model residuals every 24 hours.

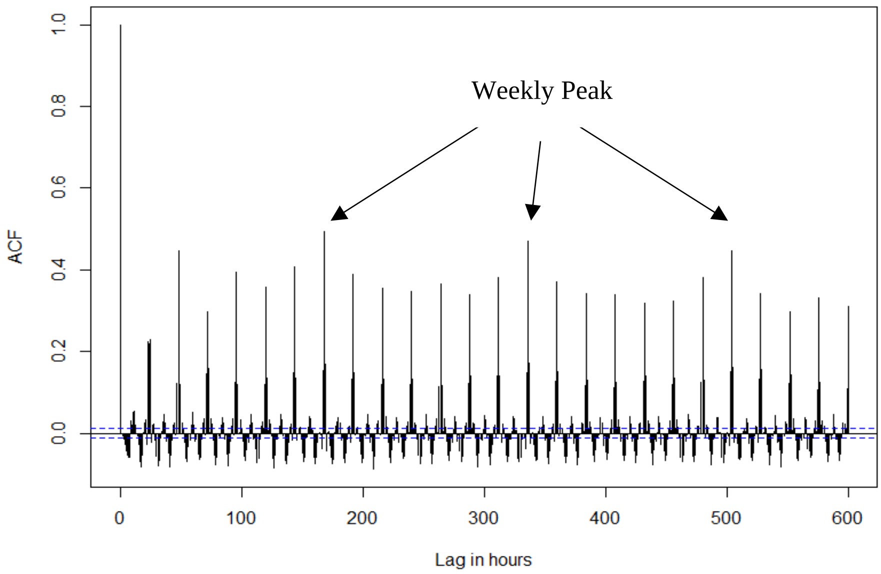

Fig. 10. ACF plot of ARIMA model residuals, 168 hours is one week

Figure 10 demonstrates the weekly nature of the residual's autocorrelation. Every 168 hours, a slightly higher peak in the autocorrelation can be detected. This peak denotes a second, weekly, seasonality factor.

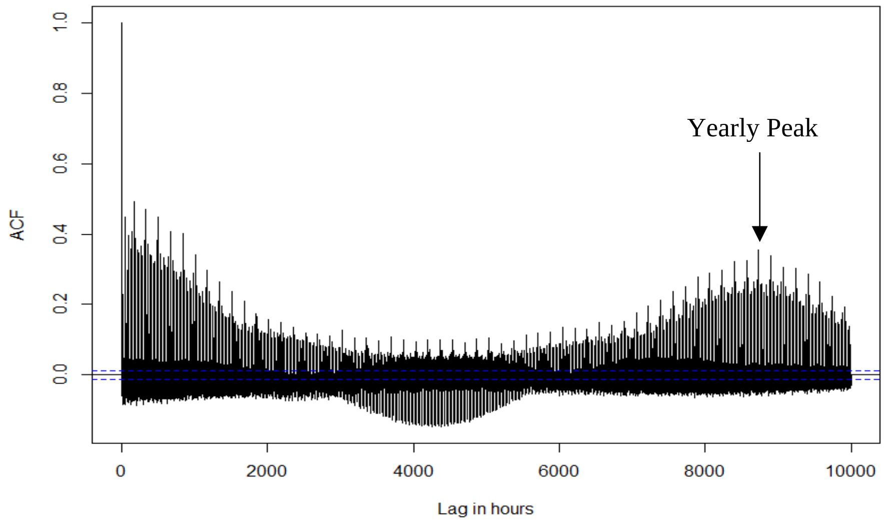

Fig. 11. ACF plot of ARIMA model residuals, 8760 hours is one year

Lastly, a third autocorrelation peak is observed in Figure 11. This peak occurs at the one-year point or 8,760 hours. This is indicative of yearly seasonality.

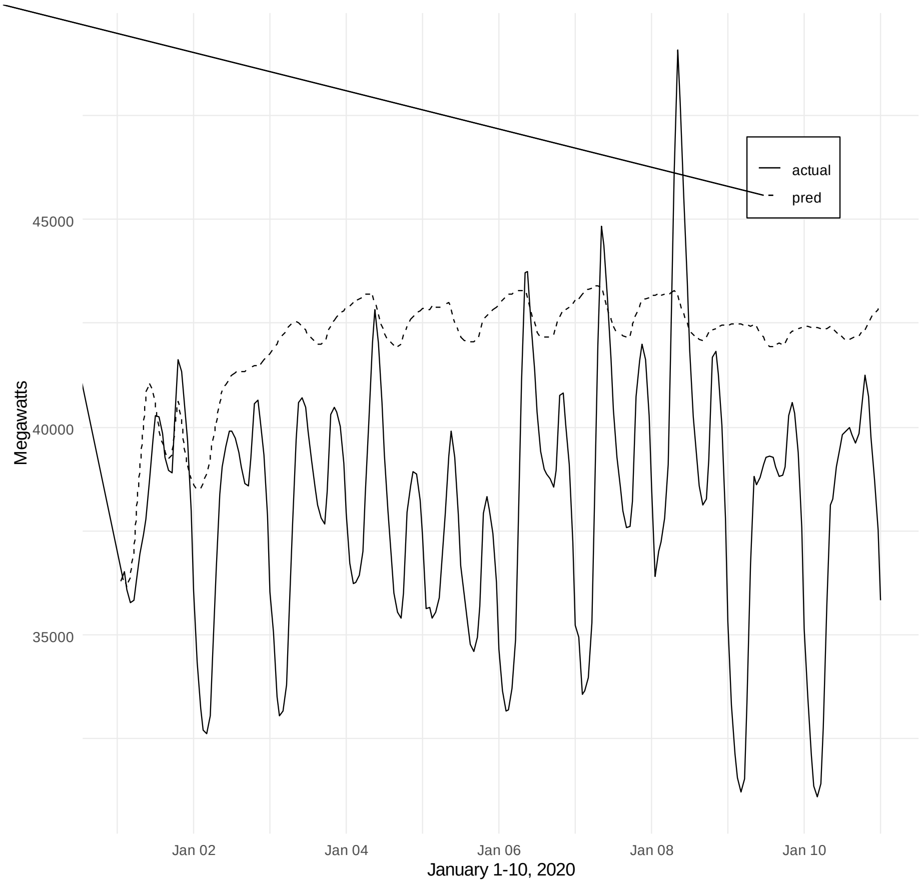

Fig.12. Actual versus predicted total power produced for the first ten days of January 2020 from arima() function

Short-term predictions derived from the ARIMA model proved to be unsatisfactory. The predictions, shown in Figure 12 by the dashed line, almost immediately regressed to the mean of the overall time-series.

Time-series Linear Regression with categorical variables for Seasonality components

Using a different function, tslm(), a model was created that utilized one hot encoded categorical variables to model the three different seasonality components of the data. This model also used the temperature score of the fourteen different weather stations as a regressive component. The temperature regression portion of the model took the following form:

$$
\begin{aligned}
PowerOutput = {} & 42537 - 13.94T_{Abilene} - 12.62T_{Amarillo} - 58.29T_{Austin} \\
& + 195.67T_{Brownsville} - 1.43T_{CorpusChristi} + 272.47T_{DFW} \\
& - 62.60T_{ElPaso} + 235.33T_{Houston} - 75.20T_{Longview} \\
& + 12.94T_{Lubbock} + 66.37T_{Midland} - 47.60T_{SanAngelo} \\
& + 203.48T_{SanAntonio} + 80.64T_{Sweetwater}
\end{aligned}
$$

Eq. 4. Equation for the Multiple Linear Regression part of the model

Interestingly in this model the three largest population centers, Houston, DFW, San Antonio, all had large positive coefficients in the temperature score portion of the model. The rest of the model is not easily displayed since it is several thousand coefficients in length.

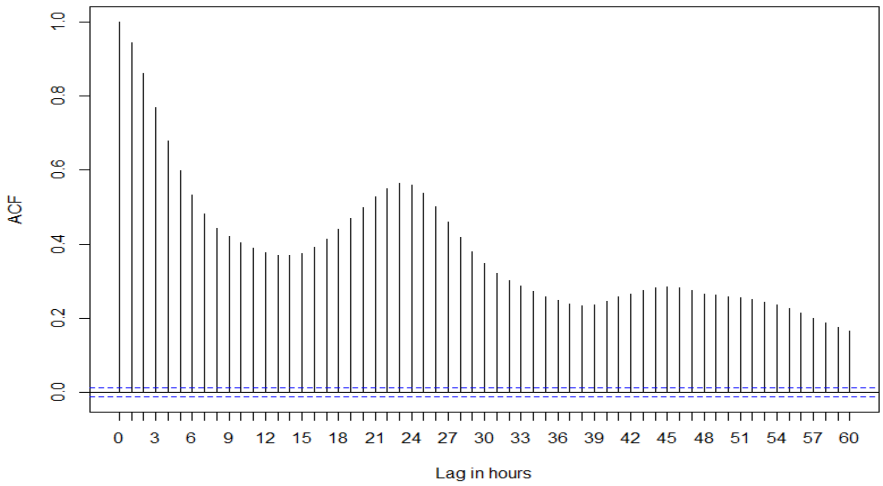

Fig. 13. Daily autocorrelation of Linear Regression Time-series residual for a model fitted with monthly, day of the week, an hour of day categories, and temperature data

Figure 13 shows the residuals for the tslm() function. This function allows the multiple seasonal components present in the data to be modeled as categorical variable. The resulting autocorellation residulas show a greatly diminished autocorrelation peak. The second peak in the graph is not even at the nominal 48-hour mark.

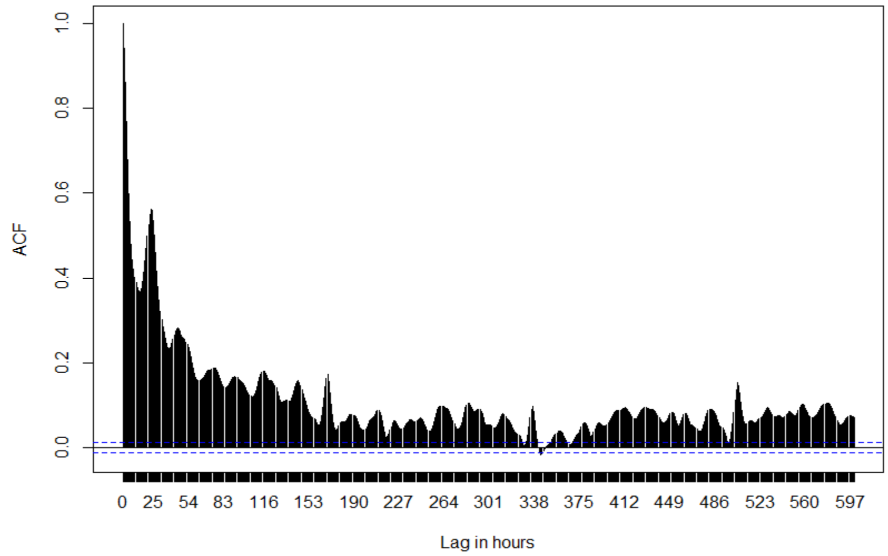

Fig. 14. Weekly autocorrelation of Linear Regression Time-series residual for a model fitted with monthly, day of the week, an hour of day categories, and temperature data

Figure 14 does still show peaks in the autocorrelation at 168-hour intervals. However, they are greatly reduced.

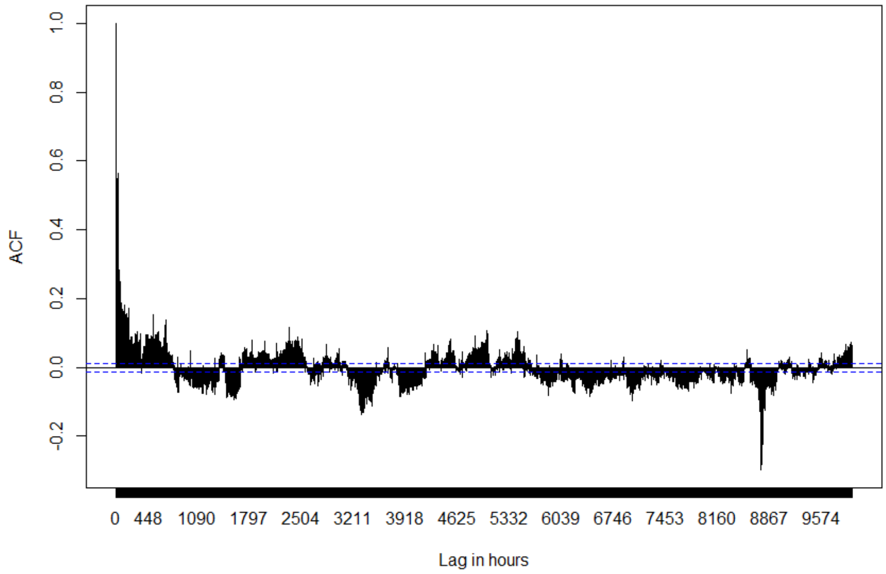

Fig. 15. Yearly autocorrelation of Linear Regression Time-series residual for a model fitted with monthly, day of the week, an hour of day categories, and temperature data

Figure 15 shows a prominent peak at the yearly 8760 intervals.

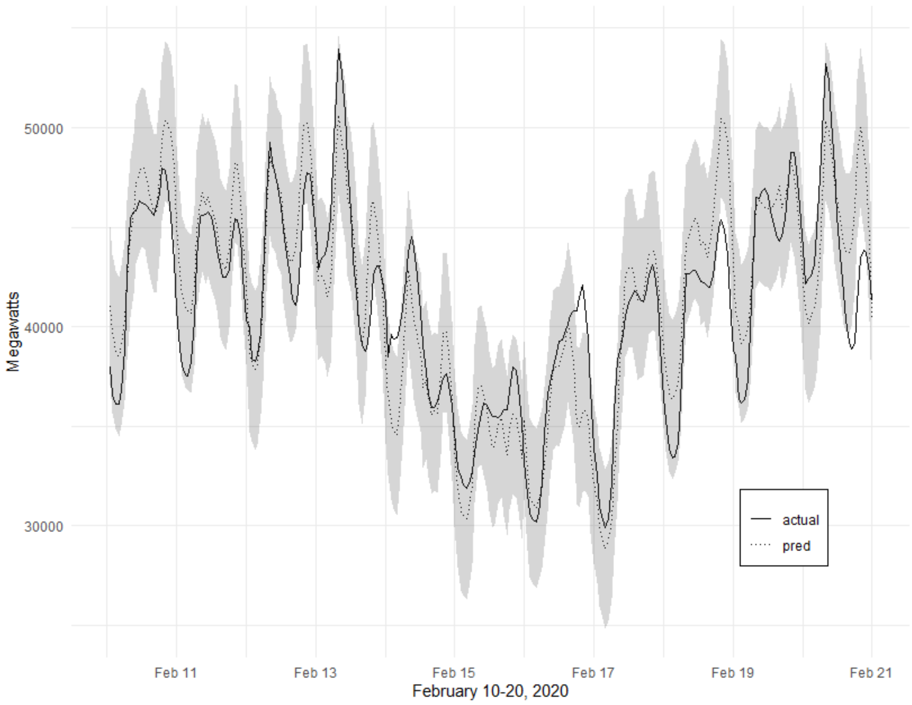

Fig. 16. Predicted versus actual demand, shaded region denotes 95% confidence range of predictions

Figure 16 shows the predicted demand as a dotted line. The ten days shown in the graph are exactly one year before the blackouts in February of 2021, the following figure shows an identical graph taken during the blackouts. The 95% confidence interval is present as the gray band. The solid line represents the actual demand. The graph shows that the actual demand stayed within the 95% confidence interval except for a few cases.

The key takeaway is that here actual demand and forecasted demand are similar in magnitude. The model provides a reasonable prediction of total power needed. The model can be used to estimate the total power needed.

Linear Regression Time-series Model applied to extreme weather events

Applying the model to the events of February 2021 gives the following result.

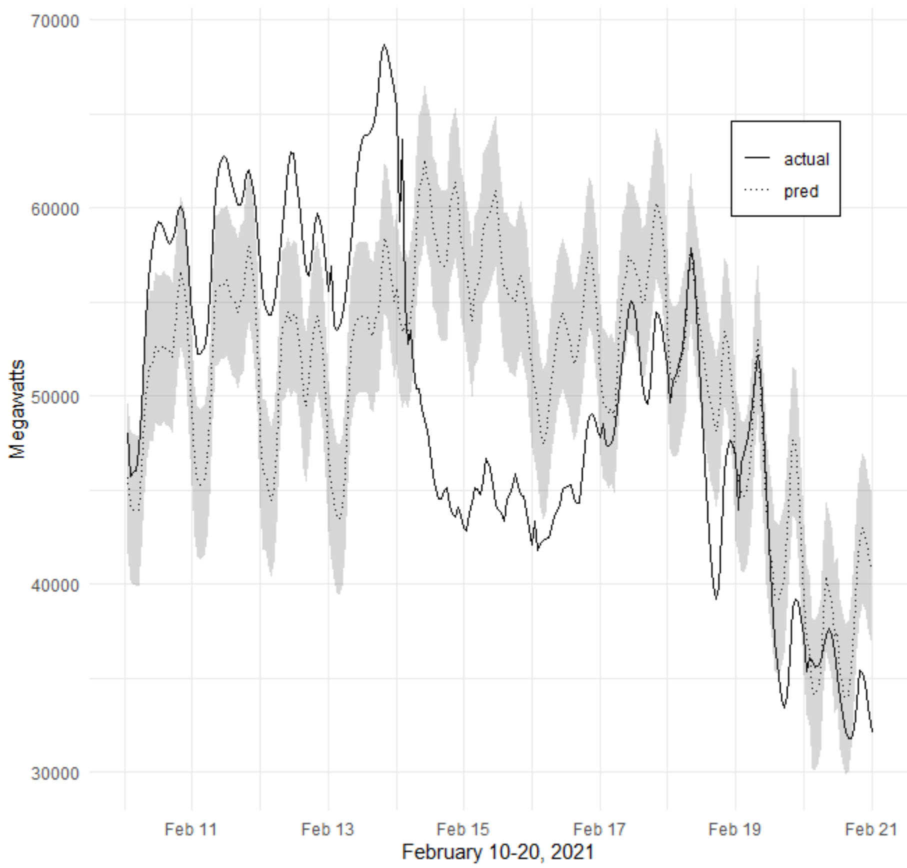

Fig. 17. Predicted versus actual demand during the blackouts of mid-February 2021, shaded region denotes 95% confidence range of predictions

During the extreme weather, the blackouts caused power deliveries to fall by different amounts. It is expected that the model would predict higher demand than the actual power delivered. However, before the blackouts began up through the 14th of February, the model predicted a lower demand than actual power delivered.

The key takeaway is that here actual demand and forecasted demand are different in magnitude. Electric demand can not be measured, only power delivered. The model can be used to estimate peak demand. The peak demand estimate shows the peak power that would have been required to avoid the blackouts

Keeping in mind, that the model is underestimating the required power by about 10 gW before the blackouts start. During February 14th the model estimates a peak demand of 63 gW. Taking into account the previously mentioned underestimation of 10 gW, a reasonable interpretation of the peak demand would be about 73 gW.

	MAPE Score training data	MAPE Score testing data
Arima() function		13.40%

Linear Regression Model		
Seasonal, Trend	6.16%	9.87%
Seasonal, Trend, Month, Weekday, Hour	5.97%	9.58%
Seasonal, Trend, Month, Weekday, Hour, Temperature	4.18%	6.41%

Tbl. 2. MAPE scores of the arima() function model and the various Linear Regression models

The MAPE scores in Table 2 show a significant improvement in the final linear regression model over the original linear regression model which lacked seasonality and regression characteristics. Comparing the final linear regression model to the original arima function model the MAPE score has been halved.

5 Discussion

Several different models were created to explain the various interactions present in the data.

5.1 Weather Data

Temperature data collected from NOAA suffered from missing values. MICE imputation gave decidedly better results than most other means of imputing missing data. Better performance could be gained by selecting several stations within the same immediate area. The locations for this study were broadly dispersed across the state. Fitting the data with MICE from local sources would result in better performance.

Additional weather data is available that could be used to create models that explain wind and solar power availability. This is a definite need for future research.

5.2 Power Data

The power data collected provides a detailed look at the overall power generated and the various sources by fuel type. The power data contained no missing data. The one item of note in the data is how little renewables contributed during the February 2021 winter storm. At times renewables accounted for less than one gW of power when the total generated was near 50 gW and actual demand was 70 to 80 gW.

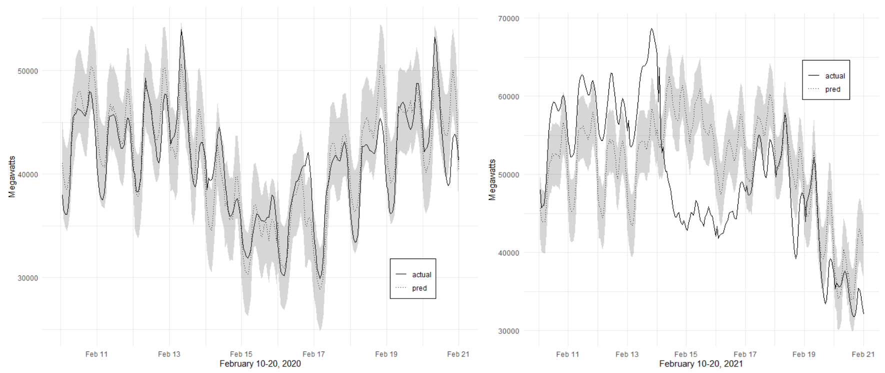

Fig. 18. Predicted and actual demand from one year before the blackouts and during the blackouts

On the left hand side of figure 18 a normal power demand and model prediction is shown. This is from one year prior to the blackouts. The figure show a mean demand of about forty gW. There is a double peak nature to the daily demand for most of the graph, that is normal behavior for this time of year. The double peak is caused by an early morning increase in electric demand as people are getting up and the temperature is usually at it's lowest point at that time. The second daily peak is at the end of the day when people arrive home but many offices and schools are still partially occupied.

The left hand side shows the effects the blackouts had on demand. The first thing to note is the average demand is at least ten gW higher than before. The double peak nature is present early in the figure but breaks down during the blackouts because all power available was being used.

5.3 Arima Function

The arima function suffers because it cannot account for multiple seasonality. The model was useful as the residuals identify the different seasonality periods present in the data. The predicted values from this model regressed immediately to the mean and thus did not provide any insight into predicting power demand.

5.4 Multiple Linear Regression Time-Series

The model results produced using linear regression are useful for predicting power demand. However, these models rely on accurate temperature forecasts. The model is only as good as the forecasts of the temperatures. Local temperature forecasts are routinely available for a rolling 48-hour period. Used with the linear regression time-series model, this will provide sufficient advance notice for scheduling generation unit availability. What this does not provide is sufficient notice for outage planning. Outtages due to generation unit maintenance can take anywhere from a day to many months, depending upon the scope of work (Ruthford, 2021). During the extremely cold weather, the model diverged significantly from the delivered power. Some of this was to be expected. The blackouts caused less power to be delivered than the actual demand called for. The model's primary purpose is to estimate this total demand during the blackouts.

The bigger issue is that prior to the 14^{th} of February, the model consistently underestimated the demand. More than likely, this is due to the "Black Swan" nature of the weather. The model does an inadequate job of predicting in the face of extreme weather. Adjustments could be made to the model. However, this would have the effect of data snooping or biasing the model based upon what the modeler thinks should happen or how they expect the model to perform.

The model obtained by this study does not work like a traditional next observation ahead predictor. Instead this model is more like a function. The input is the expected temperature at the fourteen different weather stations. The output is the expected demand. The model is only as accurate as the temperature data provided.

5.6 Renewables

During the cold weather conditions, renewables were unable to provide a significant amount of power. Looking at Figure 3, total renewable hourly power generated during the period February 10-20 never exceeded 10 gigawatts and was frequently less than 1 gigawatt. According to the model and actual power generated, demand was approximately 50 gigawatts with a maximum of 70 gigawatts, as seen in Figure 17. Not all the problems with renewable generation was caused by cold weather, lack of sunlight and lack of wind reduced available power generation as well.

5.5 Ethics

Government policy has been the primary driver determining the types of power generations installed over the last decade. The push for green energy has come at the cost of grid reliability. Solutions to compensate for the inclusion of renewable energy on the grid at scale have lagged far behind actual needs. The cost of this policy is now coming to fruition.

Is allowing further unchecked renewable energy development, even though it risks more frequent and longer blackouts, worth the risks of possible deaths and economic harm? This is a question that policymakers and consumers need to keep foremost in their minds.

6 Conclusion

Currently, the Texas electric grid is in a crisis. The recent blackouts caused by the cold weather in February 2021 are a canary in the coal mine. These blackouts demonstrate the limits of renewable energy. They also point to issues that exist with more traditional energy sources, fossil fuel and nuclear. Modeling can help determine system requirements and provides a useful guide when planning generation unit operation, even for unprecedented conditions. However, the models are only as accurate as the temperature information fed to them and suffer accuracy degradation when faced with extreme events. The models do not provide a useful guide when considering the intermediate-term, 10 to 60 days, because of inadequate temperature forecasting in that time span. This term would be most useful when outage planning.

The inability of the grid to supply enough power in February illuminates' problems with traditional sources of power. Traditional power sources are not robust when encountering extreme weather conditions. This is mainly due to fuel supplies for gas turbines. More needs to be done to provide gas turbines with alternative liquid fuel supplies during periods of peak winter use or when normal supplies of gas are interrupted. Renewable energy will need to have reliable backup power available to be of use on the grid. At this time, renewables use conventional power sources as a backup. Currently, batteries are looked at as a possible answer to this. However, batteries have yet to demonstrate a sufficient track record of reliable long-term operation, and it is unknown if they can be deployed in sufficient quantities to make an impact on grid reliability. To cope with a similar weather event, as discussed in this paper, batteries would need to deliver seventy gigawatts peak and sustain fifty gigawatts per hour for more than four days.

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