THE ENERGY GRID:
A TEXAS CASE STUDY

General Assembly Project 05
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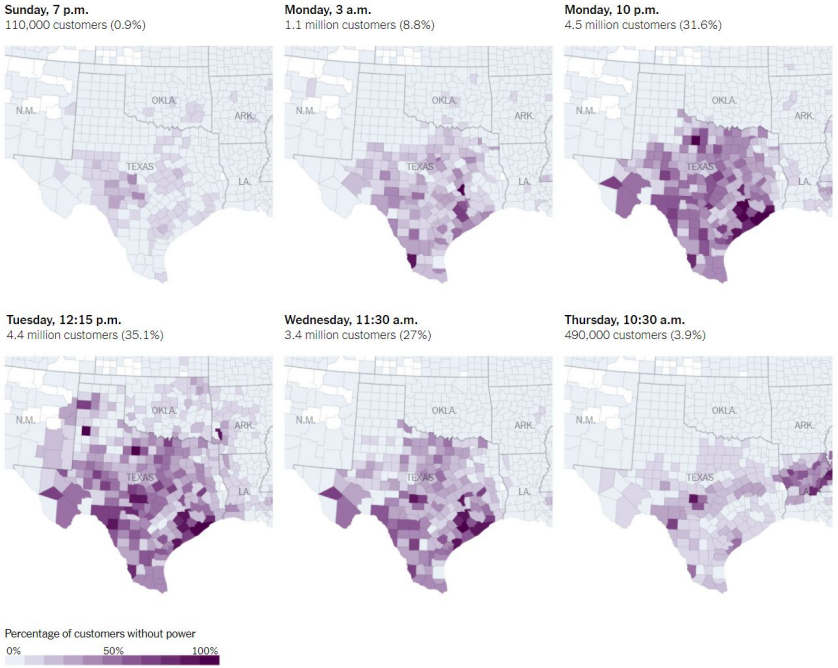
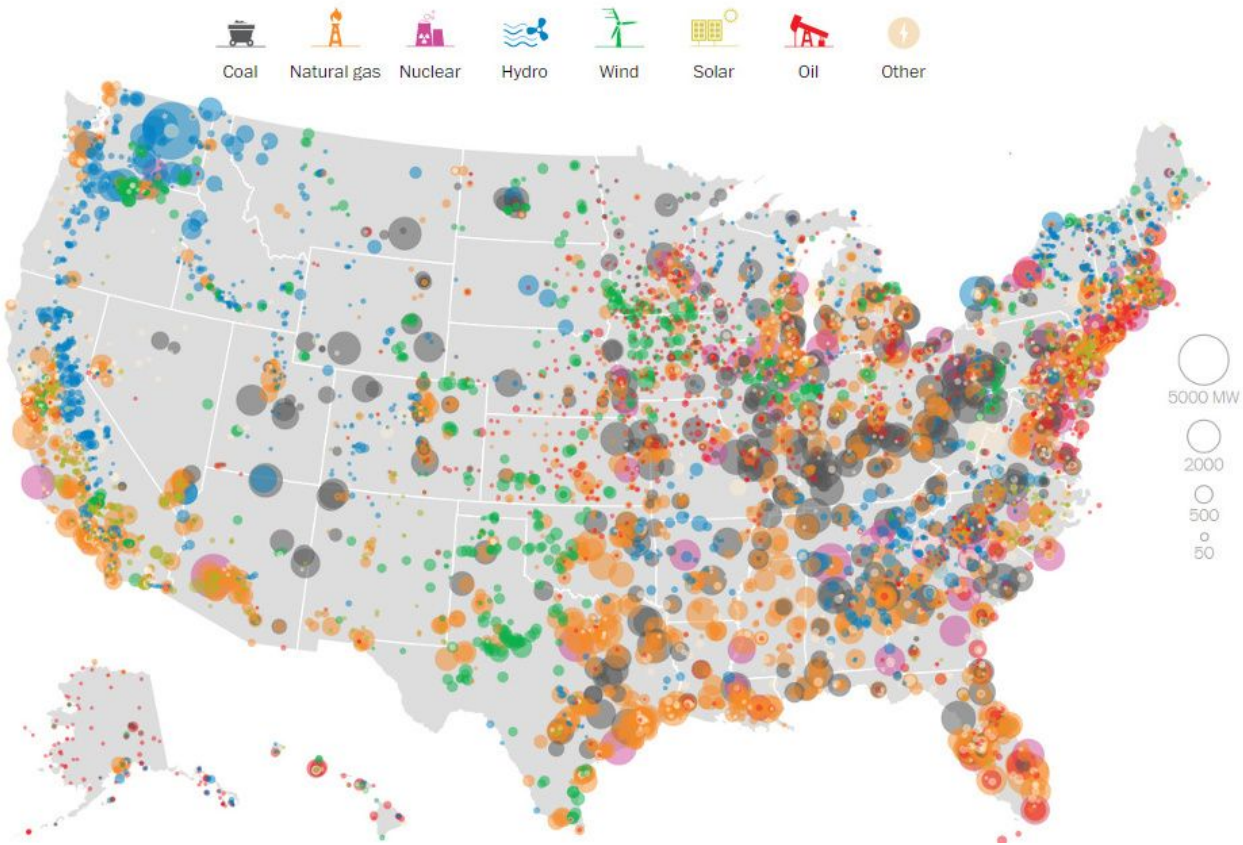
TABLE OF CONTENTS

2021 TEXAS POWER CRISIS



https://www.nytimes.com/interactive/2021/02/16/us/winter-storm-texas-power-outage-map.html https://www.sciencedirect.com/science/article/pii/S2214629621001997#f0020
https://www.popsci.com/story/environment/why-us-lose-power-storms/ https://www.statesman.com/picture-gallery/news/2021/02/14/winter-weather-texas-snow-ice-frigid-temperatures-winter-storm-uri/4483213001/



PLANT CAPACITY (MW) OF ALL POWER SOURCES IN THE US

https://www.eia.gov/energyexplained/electricity/use-of-electricity.php

https://www.visualcapitalist.com/mapping-every-power-plant-in-the-united-states/

ENERGY IN THE US

FOSSIL FUELS

40% of 2020 gen: largest

19% of 2020 gen: 3rd largest

> 1% of 2020 gen

20% of 2020 gen: 2nd largest

RENEWABLES

8.4% of 2020 gen

7.3% of 2020 gen

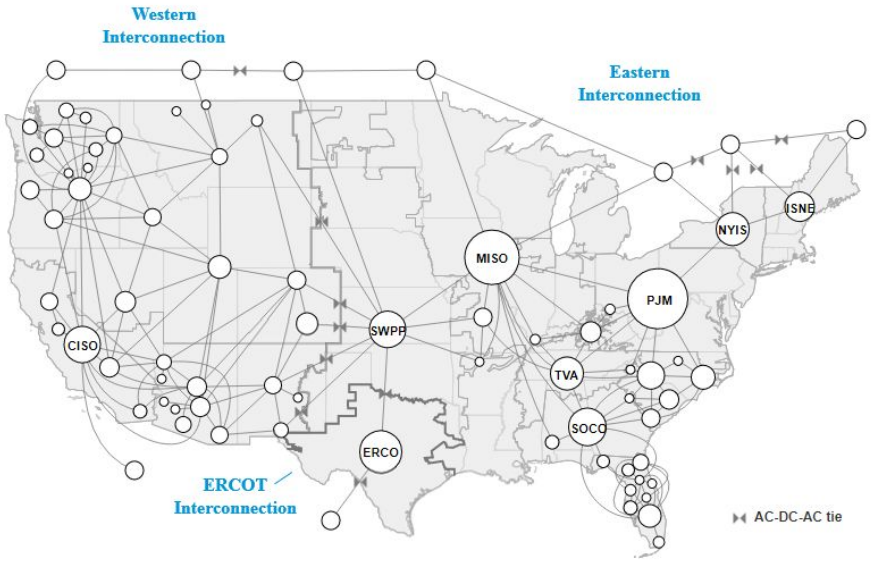
>2.3% of 2020 gen

biomass: 1.4% of 2020 gen

geothermal: 0.5% of 2020 gen

https://www.eia.gov/energyexplained/electricity/electricity-in-the-us.php
https://www.visualcapitalist.com/mapping-every-power-plant-in-the-united-states/

HOW DOES THE GRID WORK?

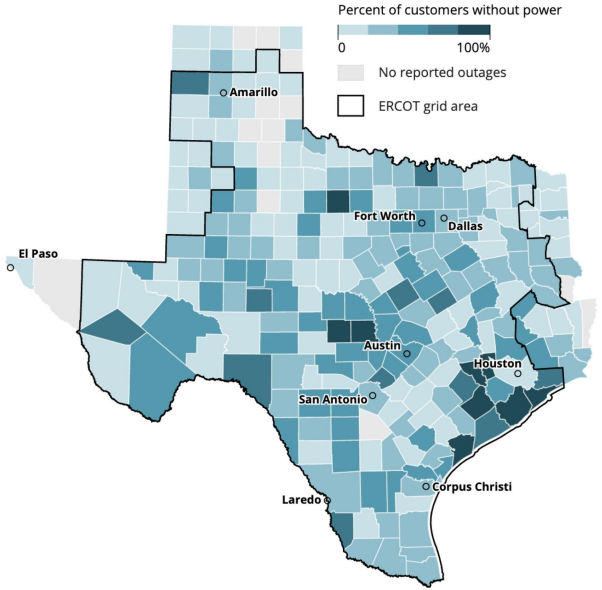


- Energy balance so supply has to meet demand
- Regional operations managed by balancing authorities (BA)
- If there is a mismatch, then BA can pull from interconnection
- 3 regions:
  - Eastern
  - Western
  - ERCOT

https://www.eia.gov/energyexplained/electricity/electricity-in-the-us-generation-capacity-and-sales.php
https://www.eia.gov/electricity/gridmonitor/about

2021 TEXAS POWER CRISIS: THE GRID

- Independent grid so limited connections to other BAs
- Did not winterize and everything was frozen
  - 40% of natural gas unavailable
  - Wind
  - Nuclear
- Demand increasing but supply was decreasing
  - Couldn't transfer electricity with other BAs
- Rolling blackouts to prevent grid collapse

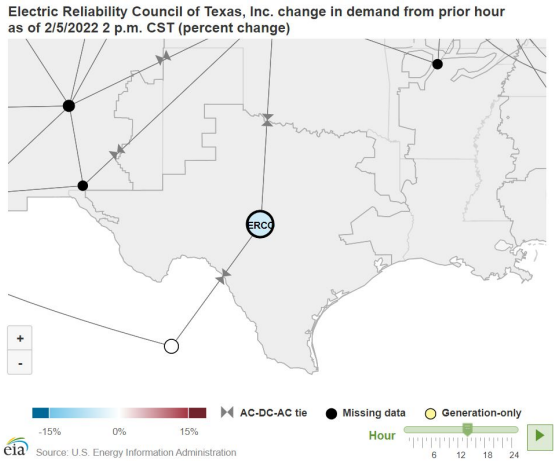


Source: The Texas Tribune and ProPublica

https://www.sciencedirect.com/science/article/pii/S2214629621001997#f0020

Can we empower people to make informed decisions about their power usage?

US EIA API



- US Energy Information Administration
- API
  - US Electric System Operating Data
    - Demand
    - Net generation
    - Net generation by energy source
    - Total interchange
    - Day-ahead demand forecast
  - By state or balancing authority
  - By time: UTC or time zone

https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/balancing_authority/ERCO https://www.eia.gov/opendata/qb.php
https://commons.wikimedia.org/wiki/File:Energy_Information_Administration_logo.svgs

DATA EXTRACTION

- From API, make function to pull date and energy (MW) for each request
- Make function that will pull info regardless of BA or query
  - Make dataframe for each plant
  - Problematic if BA doesn't draw from certain energy source

```python
def extract_energy(res):
    if res.status_code == 200:
        ts= res.json()['series'][0]['data']
        df= pd.DataFrame(ts)
    return df
```

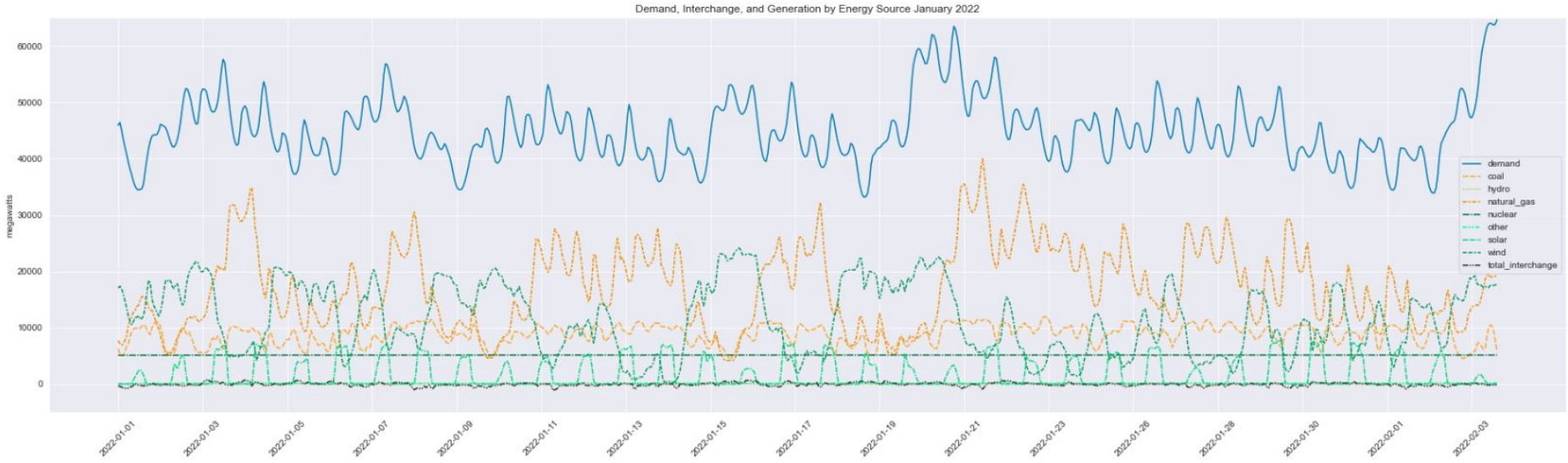
```python
def make_energy_df(api_key, plant_list, query):
    for plant in plant_list:
        url= f'http://api.eia.gov/series/?api_key={api_key}&series_id=EBA.{plant}-ALL.{query}.HL'
        res= requests.get(url)

        if 'data' not in (res.json().keys()):
            energy_df= extract_energy(res)
            return energy_df

        else:
            return 'no data'
```

MAKING THE DATASET

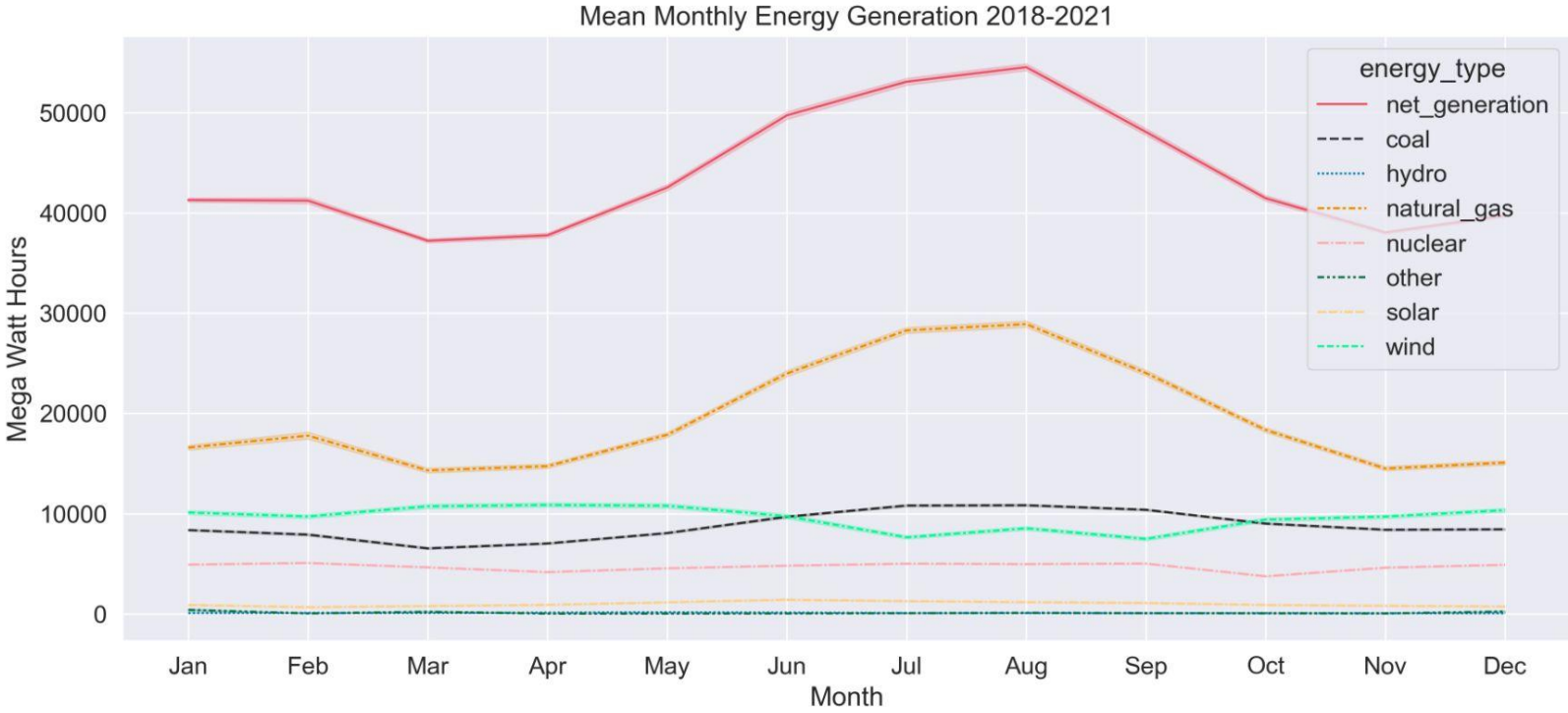
- Function would return dataframes with different datetime ranges
  - Dependent on query and when data would upload to EIA
  - Forecast predicted into the future
- Outer join to merge all dataframes on datetime column

datetime	demand	plant	net_generation	coal	hydro	natural_gas	nuclear	other	solar	wind	total_interchange	forecast
20220205T23-06	52424.0	ERCO	52179.0	9077.0	10.0	17796.0	5144.0	122.0	0.0	20030.0	-245.0	53249.0
20220205T22-06	52723.0	ERCO	52350.0	9022.0	11.0	18119.0	5143.0	128.0	0.0	19925.0	-372.0	54965.0
20220205T21-06	52136.0	ERCO	51572.0	8382.0	30.0	17950.0	5144.0	146.0	0.0	19921.0	-563.0	55162.0

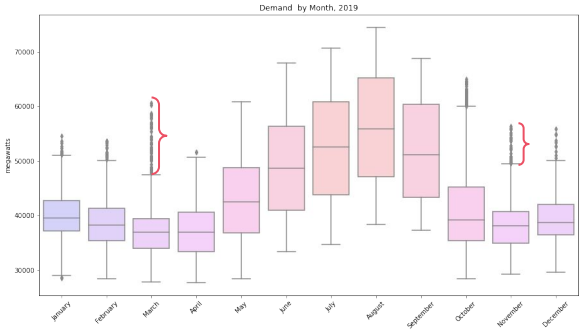
VISUALIZATING ENERGY

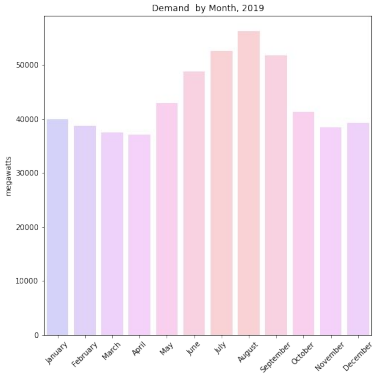


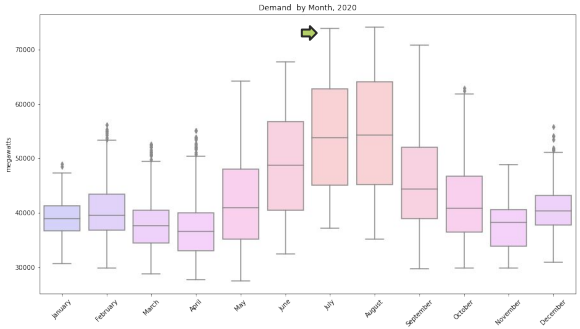
SOURCES

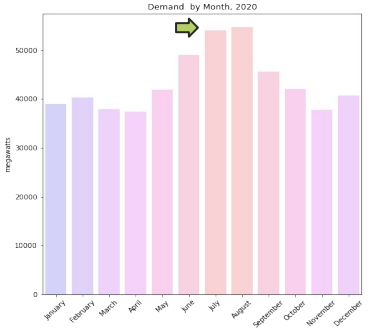

Mean Monthly Energy Generation 2018-2021
Mega Watt Hours
50000
40000
30000
20000
10000
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
energy_type
net_generation
coal
hydro
natural_gas
nuclear
other
solar
wind

DEMAND BY MONTH

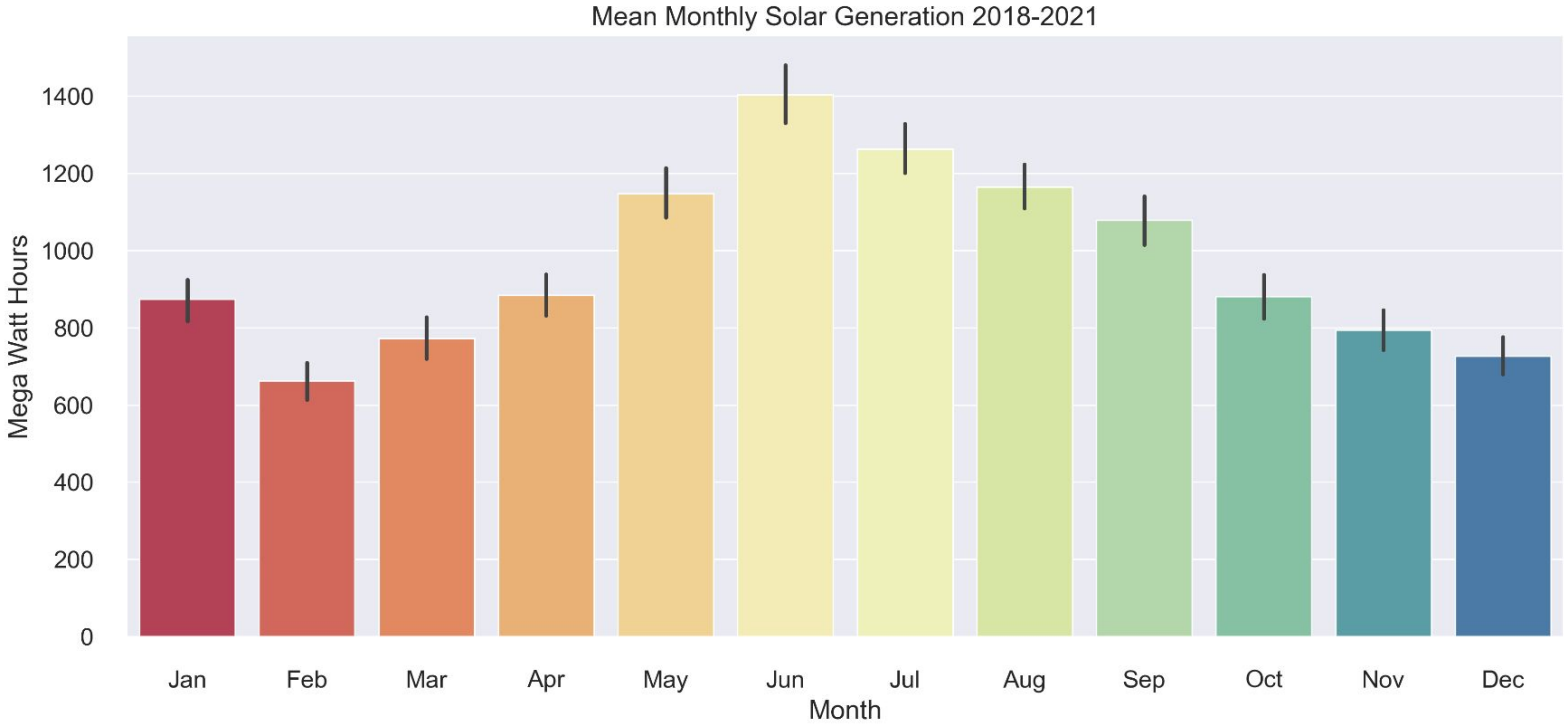




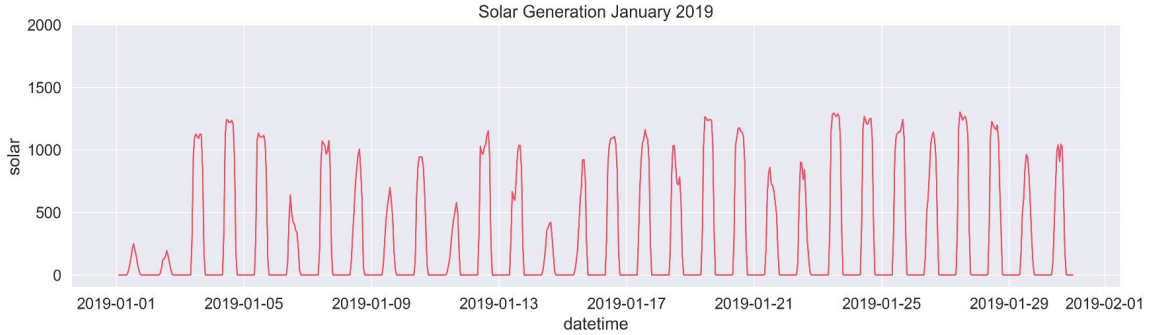


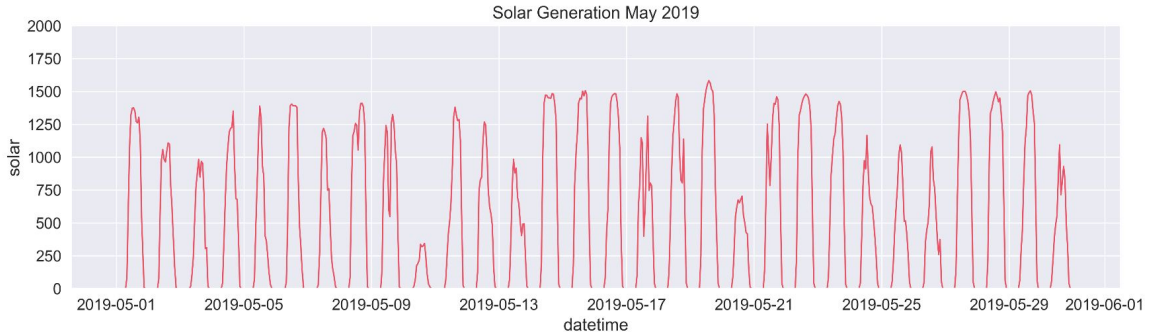


SOLAR ENERGY

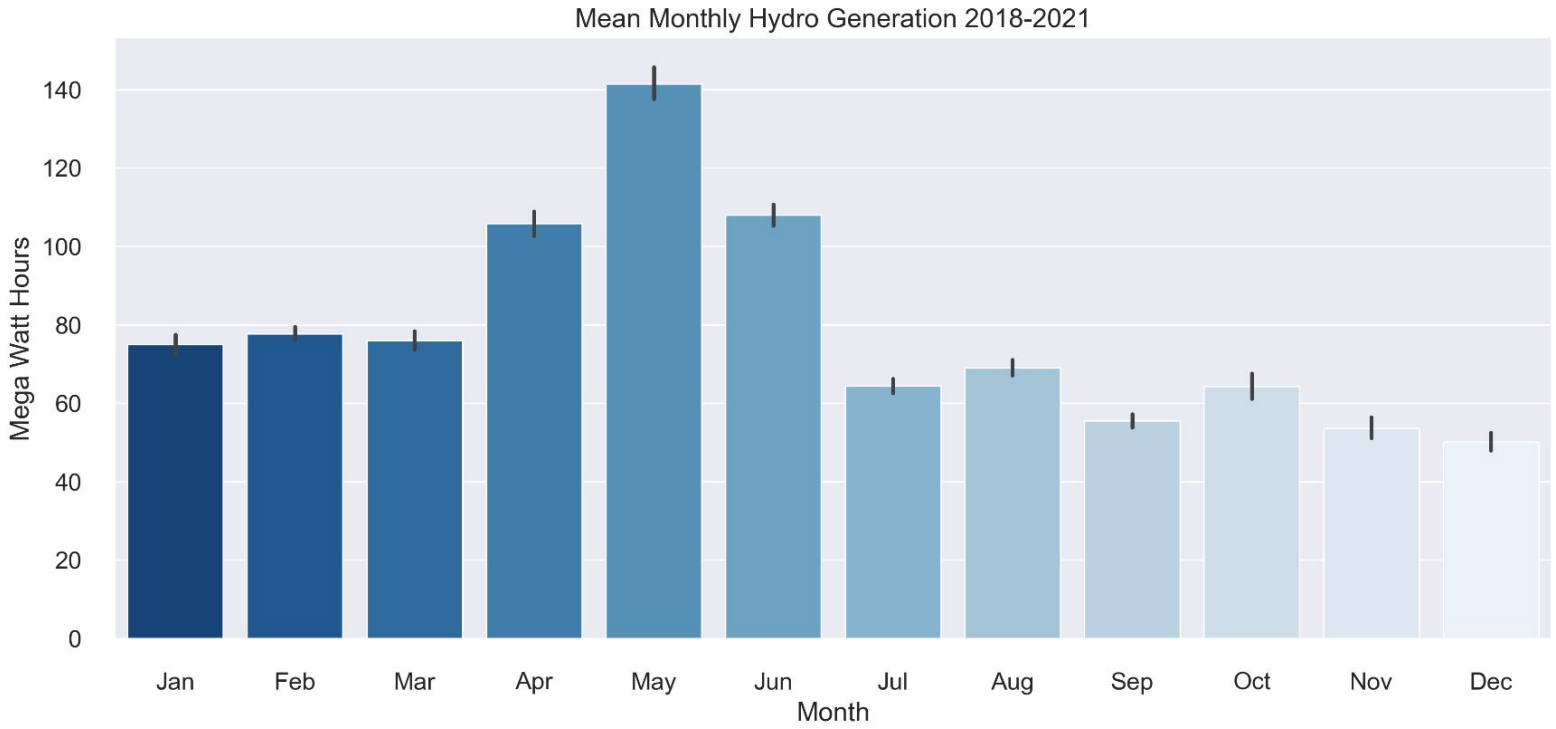


SOLAR ENERGY

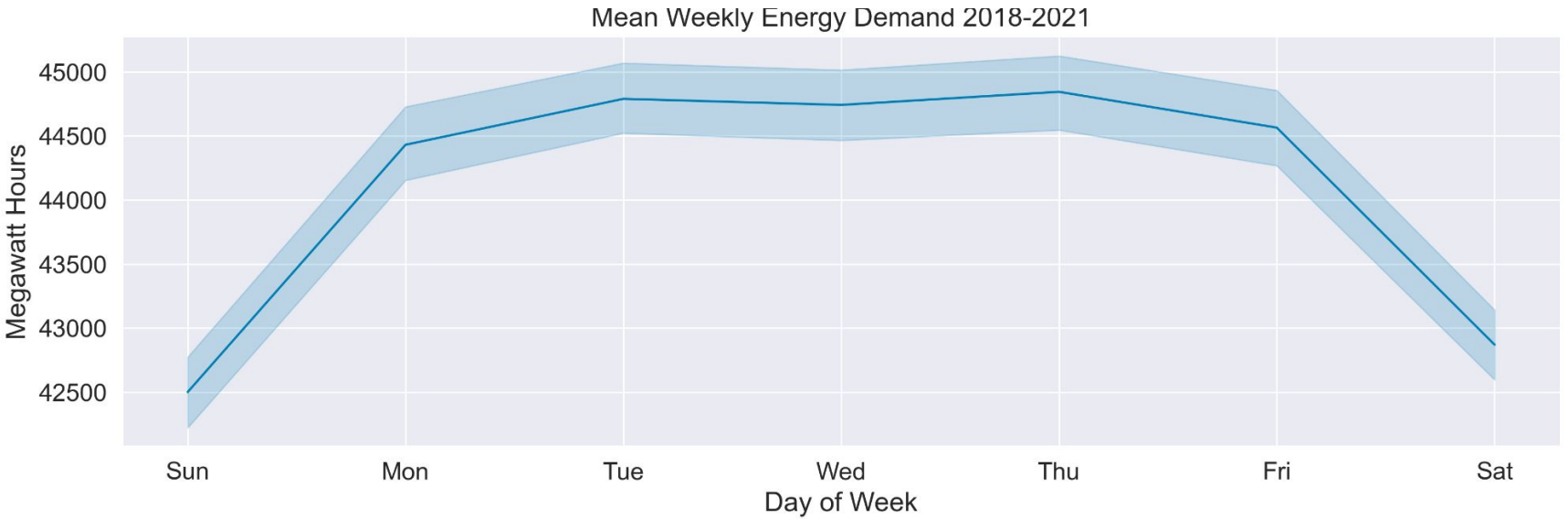




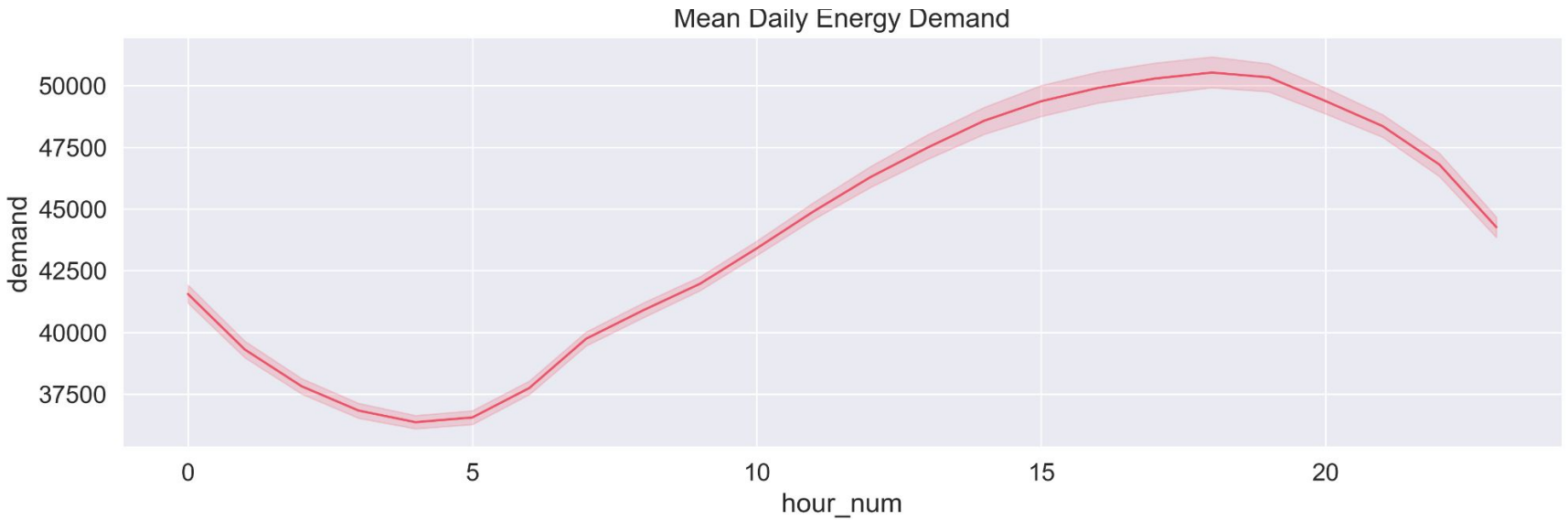
HYDRO ENERGY

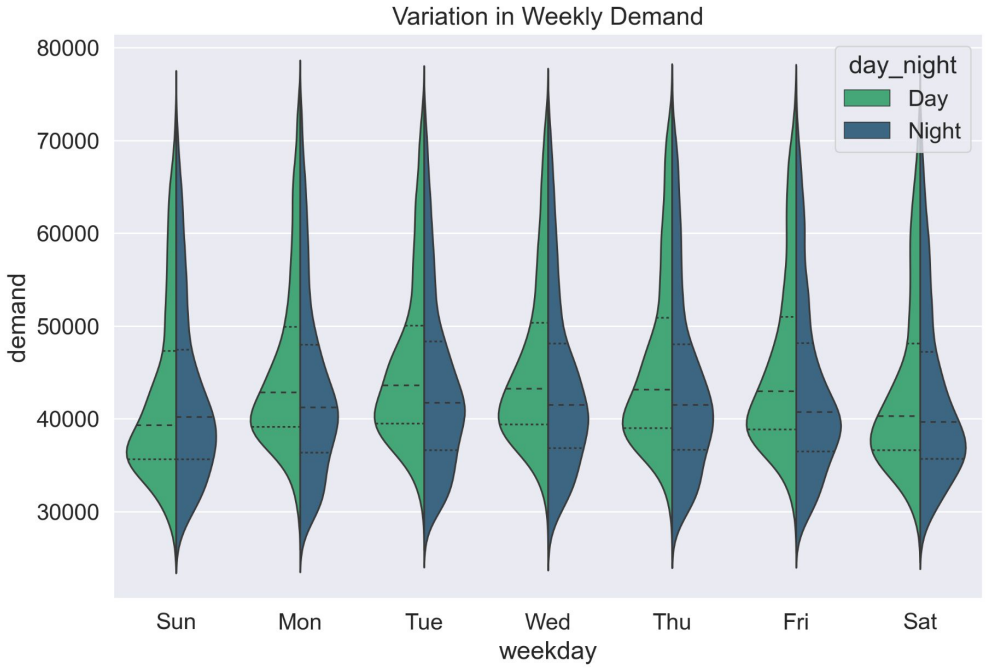


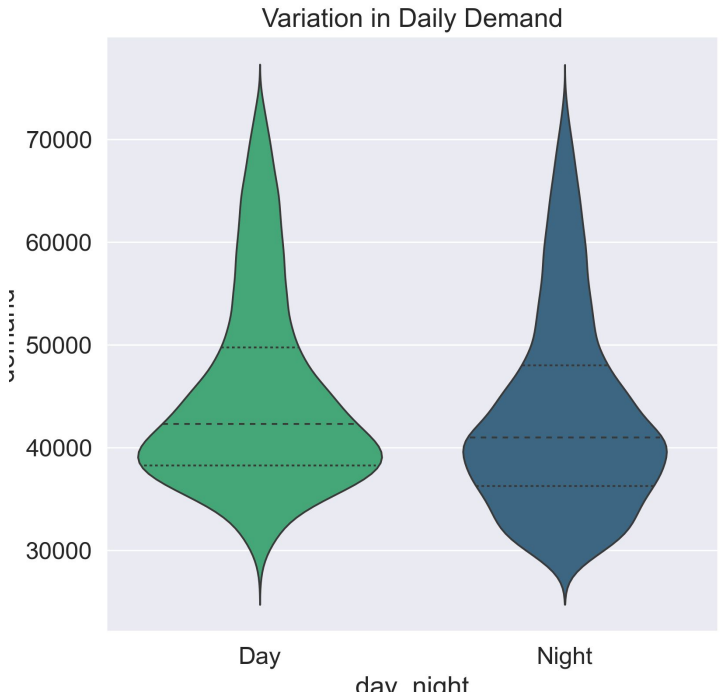
WEEKLY DEMAND

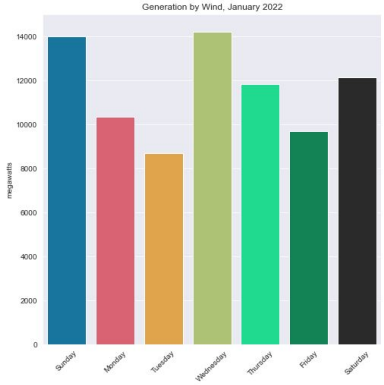


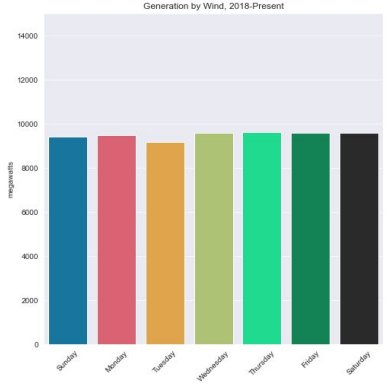
HOURLY DEMAND



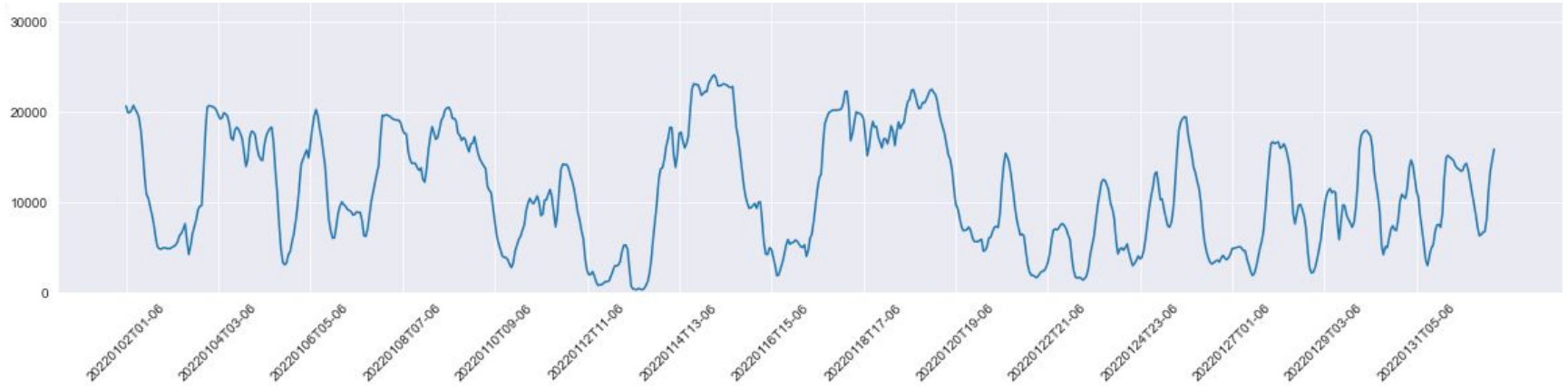

Variation in Weekly Demand
80000
70000
60000
50000
40000
30000
demand
day_night
Day
Night
Sun
Mon
Tue
Wed
Thu
Fri
Sat
weekday


Variation in Daily Demand
70000
60000
50000
40000
30000
Day
Night
day_night





WIND ENERGY

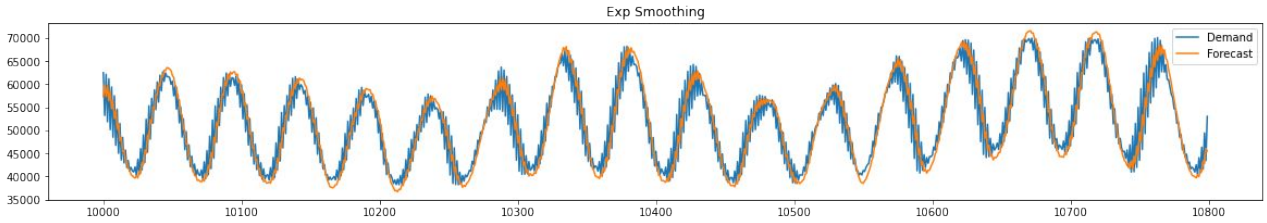


Wind Generation by Hour for January 2022

PREDICTION MODELS

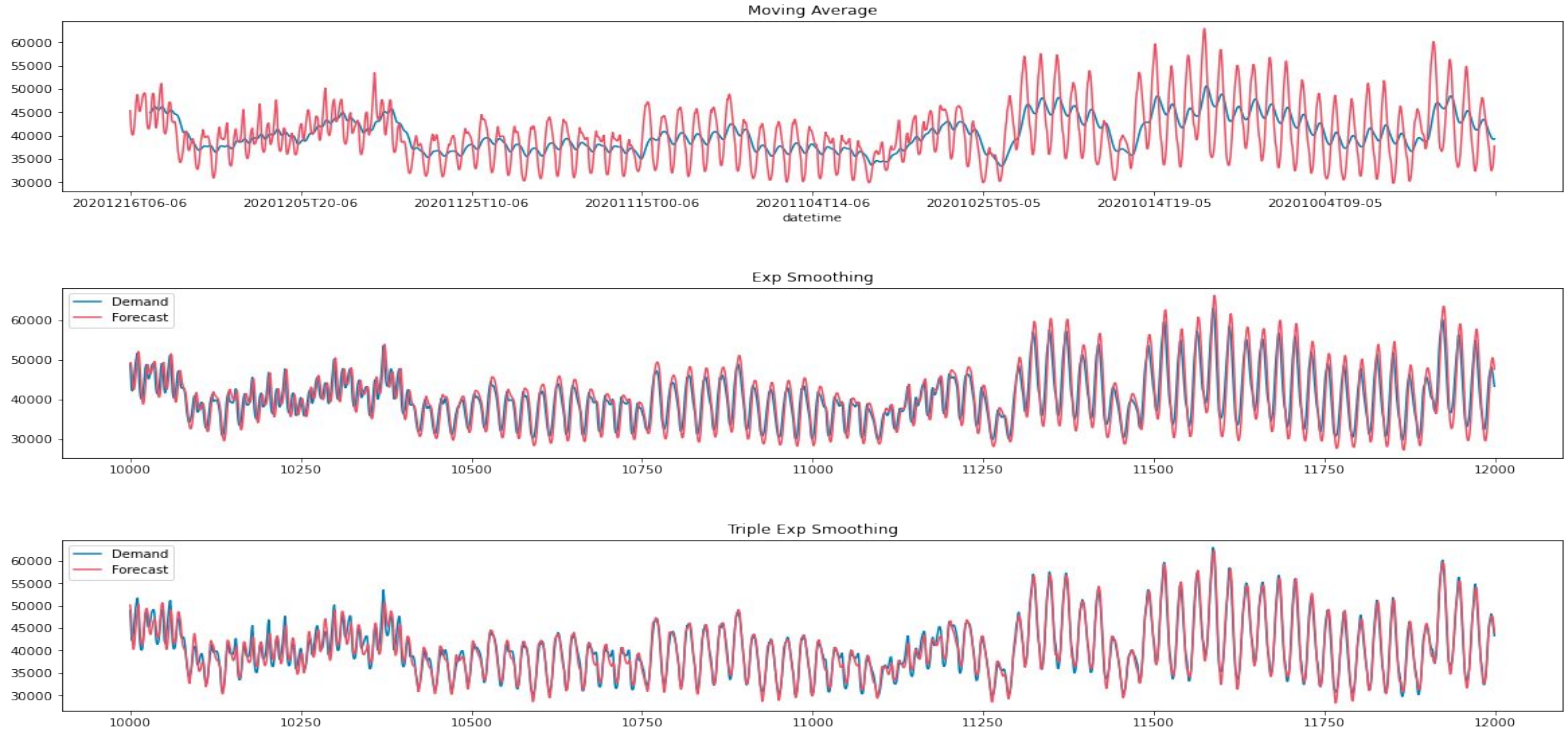
	Demand	Forecast	Level	Trend	Season	Error
0	49854.0	NaN	49592.992888	2335.096816	1.005263	NaN
1	53017.0	52778.593718	51787.983896	2138.948684	1.020970	238.406282
2	55886.0	55303.281372	53939.422742	2015.607828	1.029606	582.718628
3	57164.0	57272.511879	55711.216261	1797.145635	1.027246	-108.511879
4	55980.0	58403.765295	56376.988240	1236.767434	1.018754	-2423.765295
...	...	...	...	...	...	...
57656	32798.0	31354.061273	622.273383	-27.588762	51.732159	1443.938727
57657	33638.0	30646.118326	620.774090	-15.497649	52.162953	2991.881674
57658	35119.0	31208.226890	637.243309	-1.781043	52.533271	3910.773110
57659	37456.0	32781.824696	671.893319	12.898241	52.825122	4674.175304
57660	NaN	35496.292470	683.501736	11.608417	51.932995	NaN

- Exponential Smoothing has three basic components it measures in the dataset:
  - Level
  - Trend
  - Seasonality



https://supchains.com/ Data Science for Supply Chain Forecasting by Nicolas Vandeput

MOVING AVG TO EXP SMOOTHING



MATH BEHIND TRI-EXP SMOOTHING

```
def exp_smooth_funct(d, slen=12, extra_periods=1, alpha=0.4, beta=0.4, phi=0.9, gamma=0.3):
###Data Science for Supply Chain Management by Nicolas Vandepunt###
    cols = len(d)

    d = np.append(d,[np.nan]*extra_periods)

    f,a,b,s = np.full((4, cols+extra_periods), np.nan)
    s = seasonal_factors_mul(s,d,slen,cols)

    a[0] = d[0]/s[0]
    b[0] = d[1]/s[1] - d[0]/s[0]

    for t in range(1,slen):
        f[t] = (a[t-1] + phi*b[t-1])*s[t]
        a[t] = alpha*d[t]/s[t] + (1-alpha)*(a[t-1]+phi*b[t-1])
        b[t] = beta*(a[t]-a[t-1]) + (1-beta)*phi*b[t-1]



    for t in range(slen,cols):
        f[t] = (a[t-1] + phi*b[t-1]) * s[t-slen]
        a[t] = alpha * d[t]/s[t-slen] + (1-alpha)*(a[t-1]+phi*b[t-1])
        b[t] = beta*(a[t]-a[t-1]) + (1-beta)*phi*b[t-1]
        s[t] = gamma*d[t]/a[t] + (1-gamma)*s[t-slen]



    for t in range(cols,cols+extra_periods):
        f[t] = (a[t-1] + phi*b[t-1])*s[t-slen]
        a[t] = f[t]/s[t-slen]
        b[t] = phi*b[t-1]
        s[t] = s[t-slen]

    df_funct = pd.DataFrame.from_dict({'Demand':d,'Forecast':f,'Level':a, 'Trend':b,'Season':s,'Error':d-f})
    return df_funct
```

Our Model

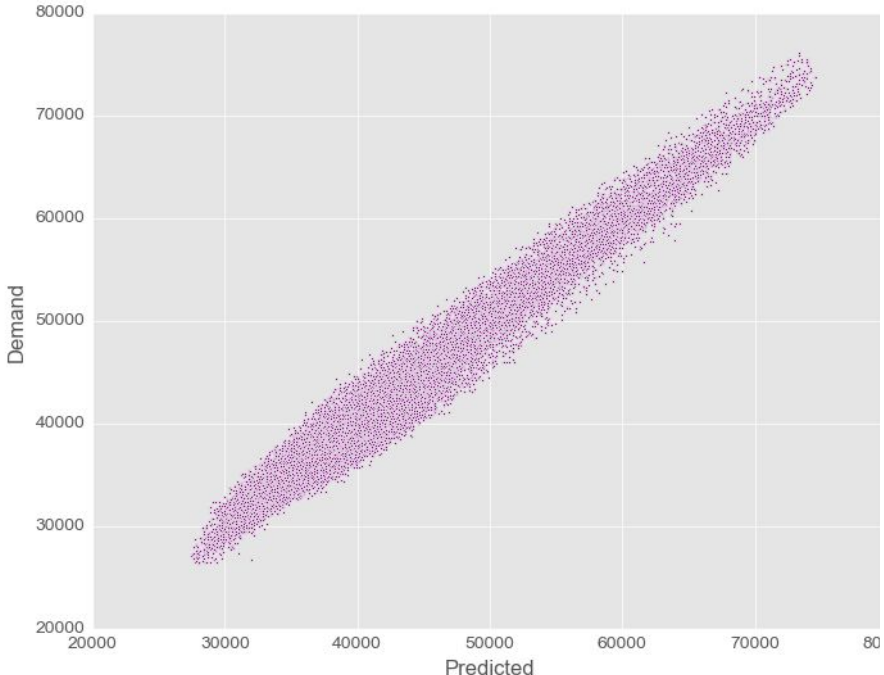
- Bias: -0.93, -0.00%
- MAE: 1337.39, 3.03%
- RMSE: 1687.98, 3.83%

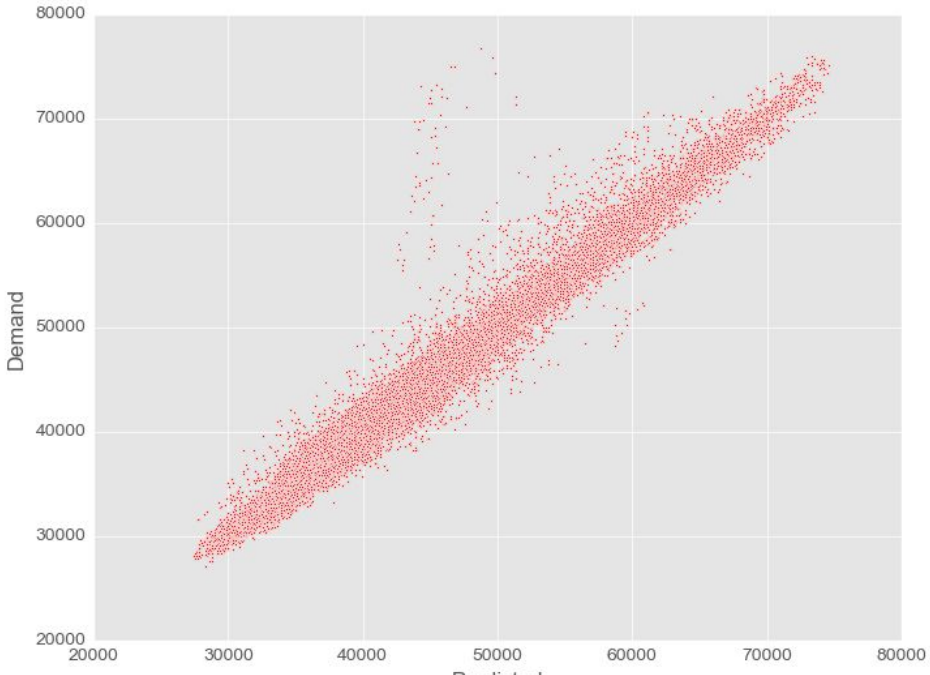
- Equal Bias (better than + still)
- Higher absolute error
- RMSE lower due to anomaly handling

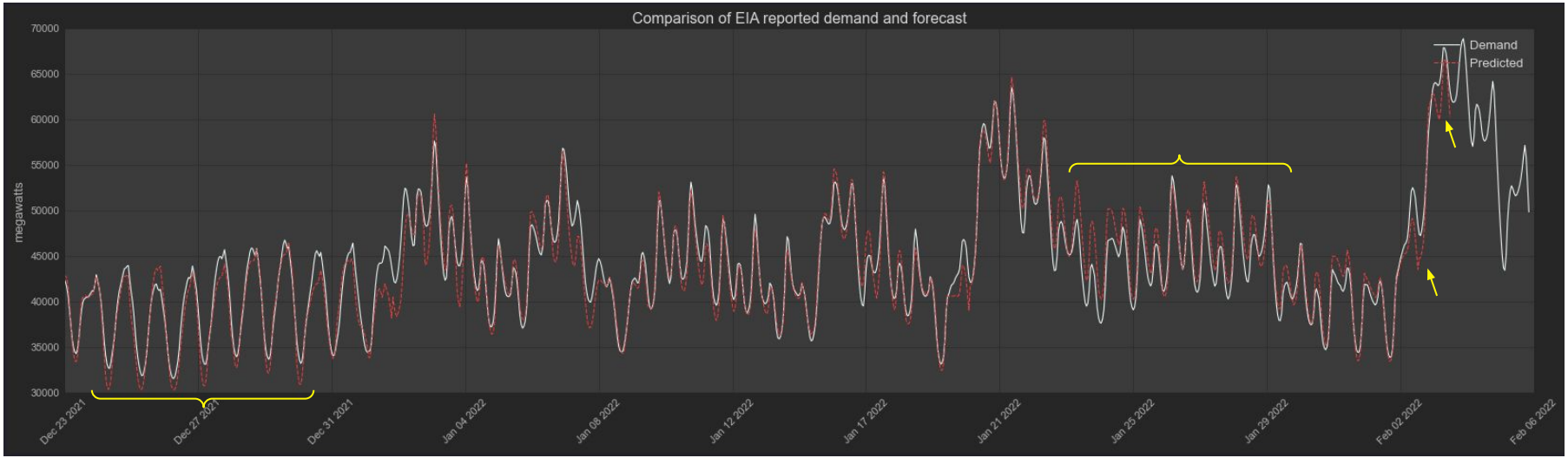
EIA 24 Hour Forecast Model

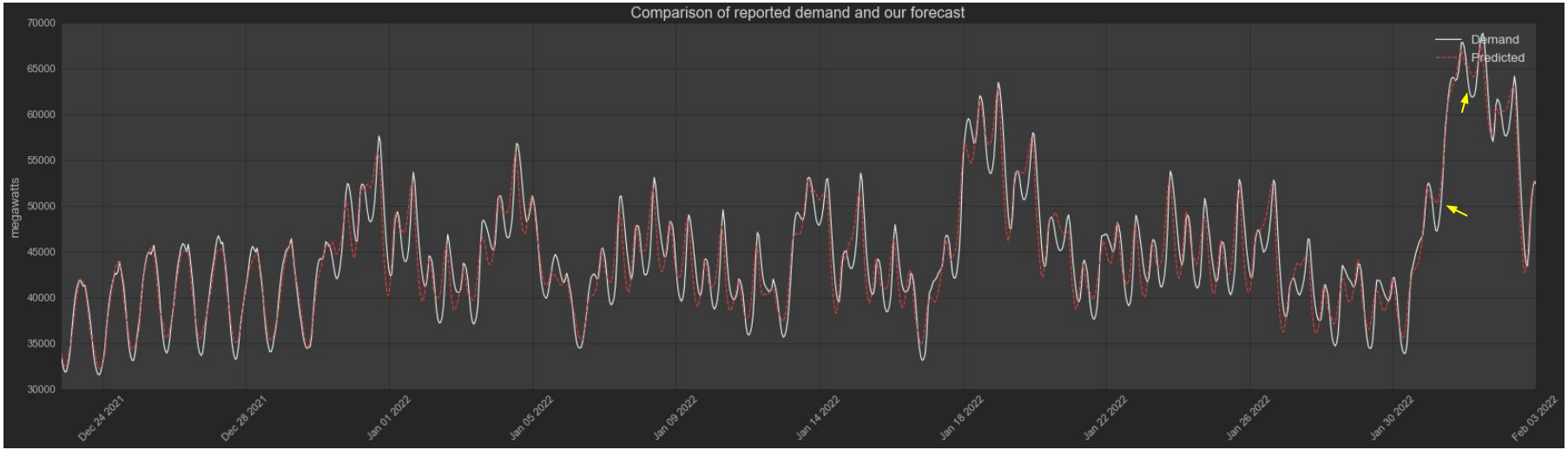
- Bias: -170.04, -0.39%
- MAE: 1099.16, 2.51%
- RMSE: 1821.58, 4.16%

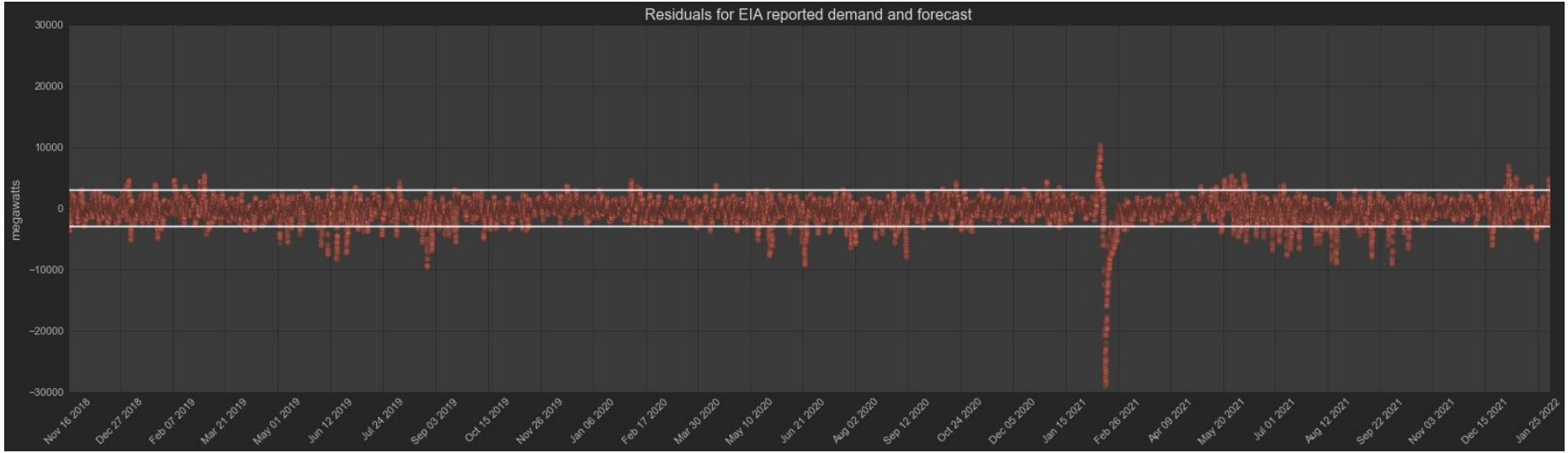
- Negative Bias (better than +)
- Better absolute error
- RMSE higher due to poor performance during anomalies

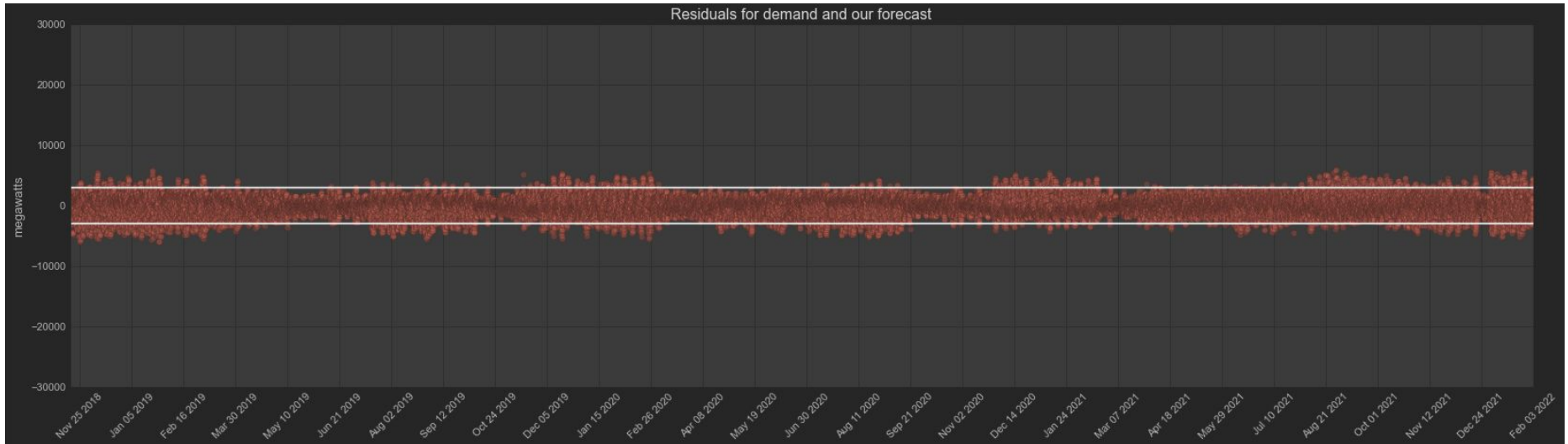





Comparison of EIA reported demand and forecast
megawatts
70000
65000
60000
55000
50000
45000
40000
35000
30000
Demand
Predicted
Dec 23 2021
Dec 27 2021
Dec 31 2021
Jan 04 2022
Jan 08 2022
Jan 12 2022
Jan 17 2022
Jan 21 2022
Jan 25 2022
Jan 29 2022
Feb 02 2022
Feb 06 2022


Comparison of reported demand and our forecast
megawatts
70000
65000
60000
55000
50000
45000
40000
35000
30000
Demand
Predicted
Dec 24 2021
Dec 28 2021
Jan 01 2022
Jan 05 2022
Jan 09 2022
Jan 14 2022
Jan 18 2022
Jan 22 2022
Jan 26 2022
Jan 30 2022
Feb 03 2022


Residuals for EIA reported demand and forecast
megawatts
30000
20000
10000
0
−10000
−20000
−30000
Nov 16 2018
Dec 27 2018
Feb 07 2019
Mar 21 2019
May 01 2019
Jun 12 2019
Jul 24 2019
Sep 03 2019
Oct 15 2019
Nov 26 2019
Jan 06 2020
Feb 17 2020
Mar 30 2020
May 10 2020
Jun 21 2020
Aug 02 2020
Sep 12 2020
Oct 24 2020
Dec 05 2020
Jan 15 2021
Feb 26 2021
Apr 09 2021
May 20 2021
Jul 01 2021
Aug 12 2021
Sep 22 2021
Nov 03 2021
Dec 15 2021
Jan 25 2022


Residuals for demand and our forecast
megawatts
30000
20000
10000
0
−10000
−20000
−30000
Nov 25 2018
Jan 05 2019
Feb 16 2019
Mar 30 2019
May 10 2019
Jun 21 2019
Aug 02 2019
Sep 12 2019
Oct 24 2019
Dec 05 2019
Jan 15 2020
Feb 26 2020
Apr 08 2020
May 19 2020
Jun 30 2020
Aug 11 2020
Sep 21 2020
Nov 02 2020
Dec 14 2020
Jan 24 2021
Mar 07 2021
Apr 18 2021
May 29 2021
Jul 10 2021
Aug 21 2021
Oct 01 2021
Nov 12 2021
Dec 24 2021
Feb 03 2022

MODEL APPLICATIONS

- Fast and scalable, as opposed to other techniques.
  - Good Choice for a streaming model
- Not as influenced by irregularities
  - over time the pattern in demand has changed
  - each year's peaks days seem to fluctuate
- Predicts 1 hour ahead of time, but could be an additional tool for power operators
  - (more accurate during irregular peaks in demand)

FUTURE GOALS

1. Obtain hourly information on residential electricity pricing
2. Train model on how forecasted demand, actual demand, and net-generation affect pricing
3. Create website (potentially Streamlit) for public to access our predictions on electricity pricing to inform their choices