Problem Statement: -

Solar power consumption has been recorded by city councils at regular intervals. The reason behind doing so is to understand how businesses are using solar power so that they can cut down on nonrenewable sources of energy and shift towards renewable energy. Based on the data, build a forecasting model and provide insights on it.

In [1]:

```
#importing required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:

solar = pd.read_csv("D:/DataScience/Class/assignment working/Forcasting/solarpower_cumuldaybyday2.csv")

In [3]:

```
solar["date"] = pd.to_datetime(solar["date"],infer_datetime_format = True)
indexed_data = solar.set_index(["date"])
```

In [4]:

```
from datetime import datetime
indexed_data.head(10)
```

Out[4]:

cum_power

| date | |
|------------|------|
| 2011-10-26 | 0.1 |
| 2011-10-27 | 10.2 |
| 2011-10-28 | 20.2 |
| 2011-10-29 | 29.6 |
| 2011-10-30 | 34.2 |
| 2011-10-31 | 38.0 |
| 2011-11-01 | 46.6 |
| 2011-11-02 | 51.6 |
| 2011-11-03 | 58.6 |
| 2011-11-04 | 60.5 |

In [5]:

indexed_data.tail()

Out[5]:

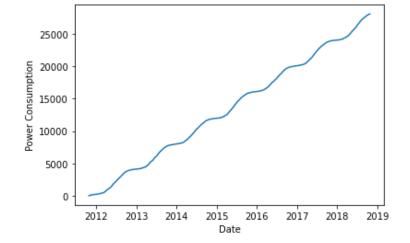
cum_power

| date | |
|------------|---------|
| 2018-10-22 | 28101.0 |
| 2018-10-23 | 28109.0 |
| 2018-10-24 | 28115.0 |
| 2018-10-25 | 28117.0 |
| 2018-10-26 | 28120.0 |

as the data is from 2011-10-26 to 2018 -10 -26 the cycle of 360 days startrts at 26th and ends at next 36th so no need to drop any rows

In [6]:

```
#plotting Graph
plt.xlabel("Date")
plt.ylabel("Power Consumption")
plt.plot(indexed_data)
plt.show()
```



Obalina Stationarity of data

Uneking Stationarity of data ths is the default requirenment for any forcasting algorithm ,the data should be stationary In [7]: pd.options.display.max_rows = 999 In [8]: pd.options.display.max columns = 100 In []: In []: In []: In []: In [10]: #checking stationarity with dicky-fuller test from statsmodels.tsa.stattools import adfuller dftest = adfuller(indexed data["cum power"], autolag = "AIC") adfoutput = pd.Series(dftest[0:4],index = ["test statastic", "p value", "lag used", "number of observations used"]) for key, value in dftest[4].items(): adfoutput["Critical value (%s)"%key]=value print(adfoutput) test statastic -0.421484 p value 0.906449 lag used 20.000000 number of observations used 2537.000000 Critical value (1%) -3.432930 -2.862680 Critical value (5%) Critical value (10%) -2.567377 dtype: float64 we can not reject null hypothesis so data is not stationary null hypothesis = data is not stationary In []: In [12]: solar.isna().sum() Out[12]: 0 date cum_power dtype: int64 In [14]: from statsmodels.graphics.tsaplots import plot acf ,plot pacf In [15]: #checking accuracy with different lags and differentiation and moving average In [18]: #normal acf and pacf plot plot_acf(indexed_data) plot_pacf(indexed_data) plt.show() Autocorrelation 1.0 0.8 0.6 0.4 0.0

-0.2

10

15

30

35

```
Partial Autocorrelation

1.0

0.8

0.6

0.4

0.2

0.0
```

In [20]:

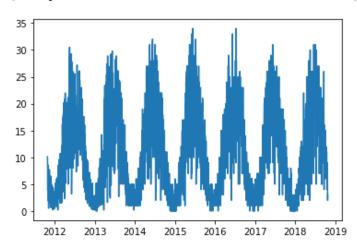
```
# first differencing
indexed_data["first_diff"] = indexed_data["cum_power"] - indexed_data["cum_power"].shift(1)
```

In [33]:

```
plt.plot(indexed_data.first_diff)
```

Out[33]:

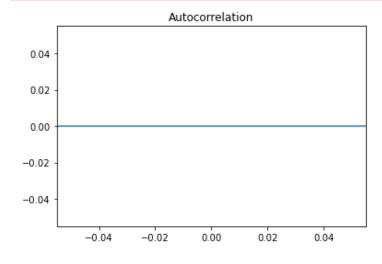
[<matplotlib.lines.Line2D at 0x208dcd0d730>]

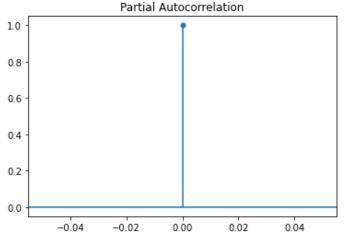


In [34]:

```
plot_acf(indexed_data.first_diff)
plot_pacf(indexed_data.first_diff)
plt.show()
```

C:\Users\theas\anaconda3\lib\site-packages\numpy\core_asarray.py:83: UserWarning: Warning: converting a masked element to nan.
return array(a, dtype, copy=False, order=order)





In [36]:

```
adfuller(indexed_data.first_diff.dropna())
```

Out[36]:

```
(-3.0856724129568414,

0.02763182430737851,

19,

2537,

{'1%': -3.4329301847920486,

'5%': -2.862679919243664,

'10%': -2.5673768219208686},

15175.367039787136)
```

```
In [41]:
# second differencing
indexed data["second diff"] = indexed data["cum power"] - indexed data["cum power"].shift(1).shift(1)
In [42]:
plt.plot(indexed data["second diff"])
Out[42]:
[<matplotlib.lines.Line2D at 0x208dc8b00d0>]
 60
 40
 30
 20
 10
                                        2019
    2012
         2013
              2014
                   2015
                        2016 2017
                                  2018
In [43]:
indexed_data["second_diff"].head()
Out[43]:
date
2011-10-26
              NaN
2011-10-27
              NaN
2011-10-28
              20.1
2011-10-29
              19.4
2011-10-30
              14.0
Name: second_diff, dtype: float64
In [44]:
adfuller(indexed_data.second_diff.dropna())
Out[44]:
(-2.965202630211606,
 0.0382743102354102,
 26,
 2529,
 {'1%': -3.432938355012086,
  '5%': -2.8626835272597217,
  '10%': -2.567378742868999},
 15251.943584943776)
In [45]:
indexed data["second diff"]
Out[45]:
date
2011-10-26
               NaN
2011-10-27
              NaN
2011-10-28
              20.1
2011-10-29
              19.4
2011-10-30
              14.0
2018-10-22
              15.0
2018-10-23
              14.0
2018-10-24
              14.0
2018-10-25
              8.0
2018-10-26
               5.0
Name: second diff, Length: 2558, dtype: float64
In [ ]:
In [53]:
#pip install pmdarima
In [55]:
from pmdarima import auto_arima
In [56]:
auto model=auto arima(indexed data.cum power, trace=True) ### returns best p,d,q values based on AIC score
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept : AIC=15320.006, Time=2.34 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept
                                   : AIC=18025.637, Time=0.07 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept : AIC=15947.568, Time=0.30 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept : AIC=16895.797, Time=0.43 sec
                                    : AIC=20652.126, Time=0.05 sec
 ARIMA(0,1,0)(0,0,0)[0]
 ARIMA(1,1,2)(0,0,0)[0] intercept : AIC=15319.616, Time=1.15 sec
 ARIMA(0,1,2)(0,0,0)[0] intercept : AIC=16517.081, Time=0.69 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept : AIC=15379.388, Time=0.88 sec
```

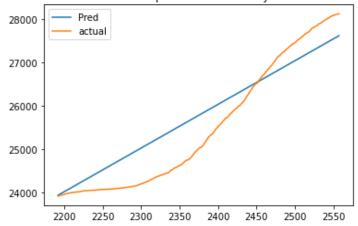
```
ARIMA(0,1,3)(0,0,0)[0] intercept
                                      : AIC=16248.109, Time=1.18 sec
 ARIMA(2,1,1)(0,0,0)[0] intercept : AIC=15318.019, Time=1.27 sec
 ARIMA(2,1,0)(0,0,0)[0] intercept : AIC=15701.892, Time=0.43 sec
 ARIMA(3,1,1)(0,0,0)[0] intercept : AIC=15320.013, Time=1.87 sec
 ARIMA(3,1,0)(0,0,0)[0] intercept : AIC=15535.761, Time=0.67 sec
 ARIMA(3,1,2)(0,0,0)[0] intercept : AIC=15320.532, Time=3.22 sec
 ARIMA(2,1,1)(0,0,0)[0]
                                       : AIC=15323.620, Time=0.64 sec
Best model: ARIMA(2,1,1)(0,0,0)[0] intercept
Total fit time: 16.754 seconds
In [57]:
auto model.summary()
Out [57]:
SARIMAX Results
                          y No. Observations:
                                               2558
   Dep. Variable:
        Model: SARIMAX(2, 1, 1)
                               Log Likelihood -7654.009
         Date:
               Sun, 04 Jul 2021
                                       AIC 15318.019
         Time:
                     14:48:18
                                       BIC 15347.252
                                      HQIC 15328.620
       Sample:
                      - 2558
Covariance Type:
                        opg
           coef std err
                          z P>|z| [0.025 0.975]
intercept 0.0635
                0.044
                       1.447 0.148 -0.023
                                         0.149
   ar.L1
         1.1941
                0.020 59.228 0.000
                                  1.155
                                        1.234
   ar.L2 -0.2001
                0.019 -10.373 0.000 -0.238 -0.162
   ma.L1 -0.8640
                0.012 -73.828 0.000 -0.887 -0.841
  sigma2 23.2928
                0.582 40.034 0.000 22.152 24.433
   Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 60.60
           Prob(Q): 1.00
                                     0.00
                             Prob(JB):
Heteroskedasticity (H): 1.10
                               Skew:
                                      0.01
  Prob(H) (two-sided): 0.17
                             Kurtosis: 3.75
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
In [171]:
df=pd.read_csv("D:/DataScience/Class/assignment working/Forcasting/solarpower_cumuldaybyday2.csv")
Building ARIMA model
In [174]:
Train = df.head(2192)
Test=df.tail(366)
In [175]:
# Creating a function to calculate the MAPE value for test data
def MAPE(pred, org):
    temp = np.abs((pred-org)/org)*100
    return np.mean(temp)
In [184]:
# Simple Exponential Method
\textbf{from statsmodels.tsa.holtwinters import } \texttt{SimpleExpSmoothing}
ses_model = SimpleExpSmoothing(Train["cum_power"]).fit(smoothing_level=1)
pred ses = ses model.predict(start = Test.index[0], end = Test.index[-1])
MAPE(pred ses, Test.cum power)
Out[184]:
5.922982997009587
In [189]:
np.sqrt(np.mean(pred ses-Test.cum power)**2)
Out[189]:
1584.4754098360656
In [186]:
# Holt method
from statsmodels.tsa.holtwinters import Holt
hw_model = Holt(Train["cum_power"]).fit(smoothing_level=0.01)
pred hw = hw model.predict(start = Test.index[0], end = Test.index[-1])
MAPE(pred hw, Test.cum power)
```

C:\Users\theas\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters\model.pv:427: FutureWarning: After 0.13 initialization must

: AIC=15320.898, Time=1.48 sec

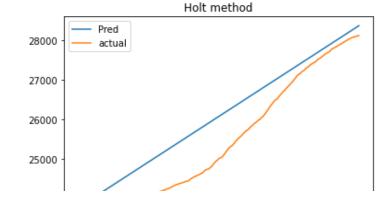
ARIMA(1,1,3)(0,0,0)[0] intercept

```
be handled at model creation
  warnings.warn(
C:\Users\theas\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters\model.py:920: ConvergenceWarning: Optimization failed to co
nverge. Check mle_retvals.
 warnings.warn(
Out[186]:
2.327441434347866
In [188]:
np.sqrt(np.mean(pred_hw-Test.cum_power)**2)
Out[188]:
576.2850881654938
In [193]:
# Holts winter exponential smoothing with additive seasonality and additive trend
from statsmodels.tsa.holtwinters import ExponentialSmoothing
hwe model add add = ExponentialSmoothing(Train["cum power"], seasonal = "add", trend = "add", seasonal periods = 2).fit(smoothing
level=0.01)
pred hwe add add = hwe model add add.predict(start = Test.index[0], end = Test.index[-1])
MAPE(pred_hwe_add_add, Test.cum_power)
Out[193]:
2.0681153138377666
In [195]:
np.sqrt(np.mean(pred hwe add add-Test.cum power) **2)
Out[195]:
427.2307160122235
In [198]:
# Holts winter exponential smoothing with multiplicative seasonality and additive trend
hwe model mul add = ExponentialSmoothing(Train["cum power"], seasonal = "mul", trend = "add", seasonal periods = 2).fit(smoothing
pred_hwe_mul_add = hwe_model_mul_add.predict(start = Test.index[0], end = Test.index[-1])
MAPE(pred_hwe_mul_add, Test.cum_power)
Out[198]:
1.9882712951755088
In [199]:
np.sqrt(np.mean(pred hwe mul add-Test.cum power) **2)
Out[199]:
275.19585296625985
In [203]:
plt.plot(pred_hwe_mul_add, label="Pred")
plt.plot(Test.cum_power, label="actual")
plt.title("multiplicative seasonality")
plt.legend()
plt.show()
                multiplicative seasonality
         Pred
 28000
         actual
 27000
 26000
 25000
 24000
```



```
In [204]:
```

```
plt.plot(pred hw,label="Pred")
plt.plot(Test.cum power, label="actual")
plt.title("Holt method")
plt.legend()
plt.show()
```



```
In [205]:
plt.plot(pred_ses, label="Pred")
plt.plot(Test.cum power, label="actual")
plt.title("Simple expo")
plt.legend()
plt.show()
                   Simple expo
         Pred
 28000
         actual
 27000
 26000
 25000
24000
      2200
           2250 2300
                    2350 2400 2450
                                  2500
Final Model
predicting for next one year
In [206]:
pred = pd.read csv("D:/DataScience/Class/assignment working/Forcasting/pred solarpower cumuldaybyday2.csv")
In [221]:
final_mod = ExponentialSmoothing(solar["cum_power"], seasonal = "mul", trend = "add", seasonal_periods = 2).fit()
C:\Users\theas\anaconda3\lib\site-packages\statsmodels\tsa\holtwinters\model.py:920: ConvergenceWarning: Optimization failed to co
nverge. Check mle_retvals.
 warnings.warn(
In [222]:
final_pred =final_mod.predict(start = pred.index[0], end = pred.index[-1])
In [223]:
plt.plot(final_pred, label="pred")
plt.plot(solar.cum_power, label="original")
plt.legend()
plt.show()
         pred
 30000
         original
 25000
 20000
 15000
 10000
 5000
   0
           500
                 1000
                      1500
                            2000
                                  2500
                                        3000
In [224]:
import statsmodels.api as sm
In [225]:
results=model.fit()
In [226]:
predic=results.predict(start = pred.index[0], end = pred.index[-1])
In [227]:
plt.plot(predic, label="pred")
plt.plot(solar.cum power, label="original")
plt.legend()
plt.show()
 30000
         pred
         original
 25000
```

24000

20000

15000

2200

2250

2300

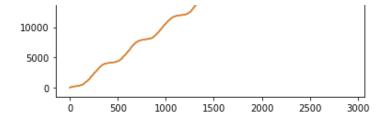
2350

2400

2450

2500

2550



Summary and inference

Im anablw to solve this problem ,as you can see the results are pathetic, i need model solution for this problem from your side, thank you

In []: