SolarPowerForecasting

June 5, 2021

1 Introduction

In this project, I am analysing the power production of solar panels. For this project, I have fetched data from Kaggle. As specified in the description, the data has been collected from the solar panels installed on the roof and the daily recordings of the power production have been recorded since October 2011 to November 2020.

For this project, I am performing and analyzing the following techniques to forecast the solar power production.

- *Moving Average*
- *Exponential Smoothing*
- *ARIMA*
- *Machine Learning*
- *LSTM (deep learning)*

1.1 Data Source

This dataset has been collected from Kaggle. Data has 4 columns namely - Date (YYYY-MM-DD), Cumulative solar power (kWh), electricity (kWh), and Gas (m^3)

1.2 Data Cleaning

Solar power production is a cumulative field. For the analysis, I have calculated daily solar power production and saved the resultant values as "Daily_Solar_Power" in the excel file.

In other words, I have five columns named as - date (YYYY-MM-DD), Cumulative_solar_power (kWh), Daily_Solar_Power (kWh), Daily_Electricity (kWh), and Daily_Gas (m^3)

1.3 Import Standard Libraries

[1]:
```
import pandas as pd #For data manipulation
import numpy as np #For numerical calculations
import matplotlib.pyplot as plt #For plotting and visualization
import sklearn.metrics as metrics #For evaluation of the performance
from sklearn.metrics import mean_squared_error #For evaluation of the␣
↪performance
from sklearn.metrics import mean_absolute_error #For evaluation of the␣
↪performance
from math import sqrt #Math function to perform square root

from sklearn.model_selection import train_test_split #To split the data into␣
↪train and test sets
from sklearn.linear_model import LinearRegression #To perform linear regression
from sklearn import preprocessing #For performing preprocessing operations
import datetime #For manipulation of date and time variables

from statsmodels.tsa.stattools import adfuller #For Adfuller test
from statsmodels.tsa.api import ExponentialSmoothing, SimpleExpSmoothing, Holt␣
↪#For exponential smoothing

from warnings import filterwarnings #To ignore warnings
filterwarnings("ignore")
```

[2]:
```
df = pd.read_excel("Solar_Power_Data_Daily.xlsx", parse_dates=True, index_col␣
↪=0) #read the data into dataframe and parse the date column
pd.options.display.float_format = '{:,.2f}'.format #to display float values␣
↪properly
```

[3]:
```
#display first 7 rows of the data
df.head(7)
```

[3]:
```
            Cumulative_solar_power  Daily_Solar_Power  Daily_Electricity  \
date
2011-10-26                    0.10               0.10              15.10
2011-10-27                   10.20              10.10               7.40
2011-10-28                   20.20              10.00               5.80
2011-10-29                   29.60               9.40               4.90
2011-10-30                   34.20               4.60              11.70
2011-10-31                   38.00               3.80              11.00
2011-11-01                   46.60               8.60               3.50

            Daily_Gas
date
2011-10-26       9.00
2011-10-27       9.20
```

```
2011-10-28       8.00
2011-10-29       6.60
2011-10-30       5.30
2011-10-31       5.70
2011-11-01       5.30
```

[4]:
```
df.shape #display the shape of the dataframe
```

[4]:
```
(3304, 4)
```

[5]:
```
df.dtypes
```

[5]:
```
Cumulative_solar_power    float64
Daily_Solar_Power         float64
Daily_Electricity         float64
Daily_Gas                 float64
dtype: object
```

[6]:
```
df=df.drop(["Cumulative_solar_power","Daily_Electricity","Daily_Gas"],1)
```

[7]:
```
df.head()
```

[7]:
```
            Daily_Solar_Power
date
2011-10-26               0.10
2011-10-27              10.10
2011-10-28              10.00
2011-10-29               9.40
2011-10-30               4.60
```

1.4 Part 1: Simple Moving Average: Window = 7

In this part, we are calculating the SMA over a period of 7 days.

[8]:
```
# the simple moving average over a period of 7
df['SMA_7'] = df["Daily_Solar_Power"].rolling(window=7).mean()
```

[9]:
```
df.tail(15) #displaying the last 15 rows
```

[9]:
```
            Daily_Solar_Power  SMA_7
date
2020-10-27               4.00   4.29
2020-10-28               3.00   4.43
2020-10-29               4.00   4.14
2020-10-30               3.00   3.86
2020-10-31               3.00   3.14
2020-11-01               4.00   3.29
```

```
2020-11-02                 3.00   3.43
2020-11-03                 2.00   3.14
2020-11-04                 6.00   3.57
2020-11-05                 7.00   4.00
2020-11-06                 8.00   4.71
2020-11-07                 8.00   5.43
2020-11-08                 8.00   6.00
2020-11-09                 5.00   6.29
2020-11-10                 3.00   6.43
```

[10]:
```
df['Error_7']=df["Daily_Solar_Power"]-df['SMA_7']
#Calculate Error, i.e., calculate deviation from the actual values
```

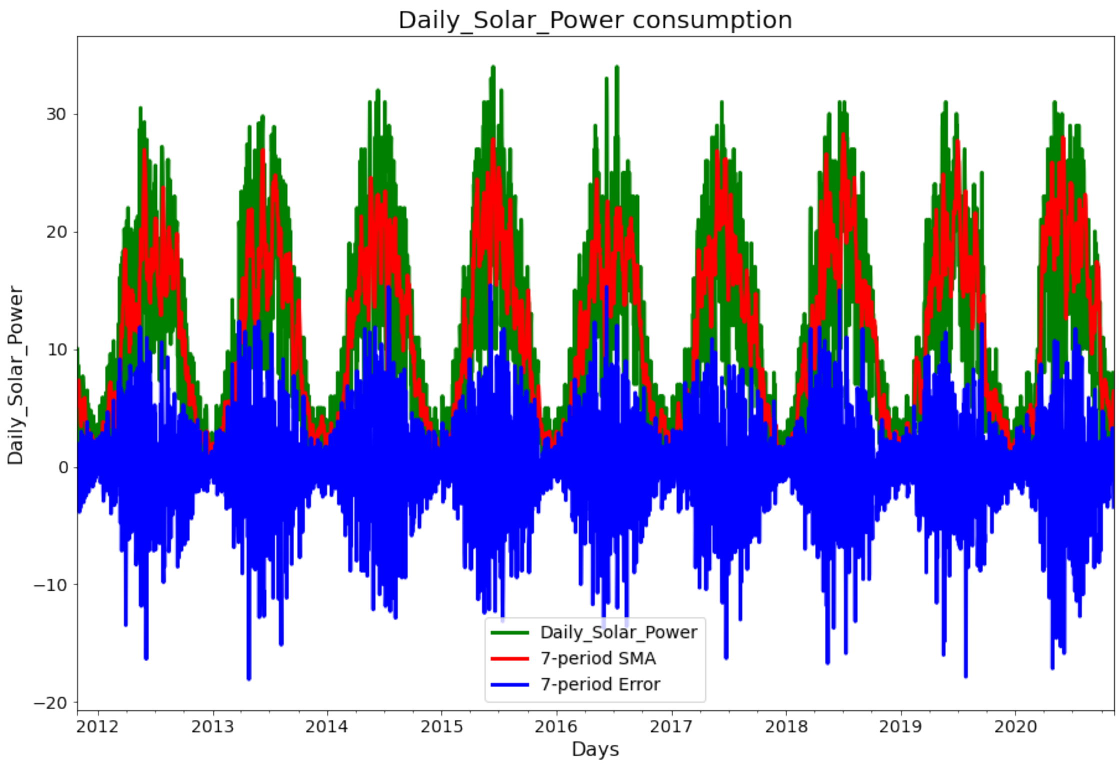
[11]:
```
df.tail(15) #Display the dataframe
```

[11]:
```
            Daily_Solar_Power  SMA_7  Error_7
date
2020-10-27                 4.00   4.29    -0.29
2020-10-28                 3.00   4.43    -1.43
2020-10-29                 4.00   4.14    -0.14
2020-10-30                 3.00   3.86    -0.86
2020-10-31                 3.00   3.14    -0.14
2020-11-01                 4.00   3.29     0.71
2020-11-02                 3.00   3.43    -0.43
2020-11-03                 2.00   3.14    -1.14
2020-11-04                 6.00   3.57     2.43
2020-11-05                 7.00   4.00     3.00
2020-11-06                 8.00   4.71     3.29
2020-11-07                 8.00   5.43     2.57
2020-11-08                 8.00   6.00     2.00
2020-11-09                 5.00   6.29    -1.29
2020-11-10                 3.00   6.43    -3.43
```

Plot of Moving Average graph

[12]:
```
# colors for the line plot
colors = ['green', 'red', 'blue']

# line plot for Stock_Exchange
df.plot(color=colors, linewidth=3, figsize=(15,10))

# modify ticks size
plt.xticks(fontsize=14) #set x ticks
plt.yticks(fontsize=14) #set y ticks
plt.legend(labels =["Daily_Solar_Power", '7-period SMA', '7-period Error'],␣
 ↪fontsize=14) #set the legends
```

```
# title and labels
plt.title("Daily_Solar_Power consumption", fontsize=20) #set the title
plt.xlabel('Days', fontsize=16) #set x label
plt.ylabel("Daily_Solar_Power", fontsize=16) #set y label
plt.show() #show the plot
```



Evaluate the Performance of Simple Moving Average

[13]:
```
# For KPI Calculation
MAE_train=df["Error_7"].abs().mean()/df["Daily_Solar_Power"].abs().mean()
print("MAE%:", round(MAE_train*100,1))

RMSE = np.sqrt((df["Error_7"]**2).mean())
print("RMSE:",round(RMSE,2))
```

```
MAE%: 28.9
RMSE: 4.32
```

1.4.1 Conclusion for Simple Moving Average

The idea behind the evaluation of optimum forecast is that its deviation from the actual value should be minimum. This deviation is measured in terms of error which is Root Mean Squared Error (RMSE). The value in our case is 4.32, which seems good to forecast the solar power production.

1.5 Part 2: Exponential Smoothing

In this part, I am calculating Simple Exponential Smoothing, Double Exponential Smoothing, and Triple Exponential Smoothing.

1.5.1 Split the Data into Training and Test sets for SES, DES, and TES

[14]:
```
df = pd.read_excel("Solar_Power_Data_Daily.xlsx", parse_dates=True, index_col␣
↪=0) #read the data into dataframe and parse the date column
pd.options.display.float_format = '{:,.2f}'.format #to display float values␣
↪properly
```

[15]:
```
df.head() #display the first 5 rows of the data
```

[15]:
```
            Cumulative_solar_power  Daily_Solar_Power  Daily_Electricity  \
date
2011-10-26                    0.10               0.10              15.10
2011-10-27                   10.20              10.10               7.40
2011-10-28                   20.20              10.00               5.80
2011-10-29                   29.60               9.40               4.90
2011-10-30                   34.20               4.60              11.70

            Daily_Gas
date
2011-10-26       9.00
2011-10-27       9.20
2011-10-28       8.00
2011-10-29       6.60
2011-10-30       5.30
```

[16]:
```
df=df.drop(["Cumulative_solar_power","Daily_Electricity","Daily_Gas"],1)

df.head()
```

[16]:
```
            Daily_Solar_Power
date
2011-10-26               0.10
2011-10-27              10.10
2011-10-28              10.00
2011-10-29               9.40
2011-10-30               4.60
```

[17]:
```
df=df.filter(like='2020',axis=0)
```

[18]:
```
df.head()
```

[18]:
```
            Daily_Solar_Power
date
```

```
2020-01-01              2.00
2020-01-02              1.00
2020-01-03              1.00
2020-01-04              1.00
2020-01-05              1.00
```

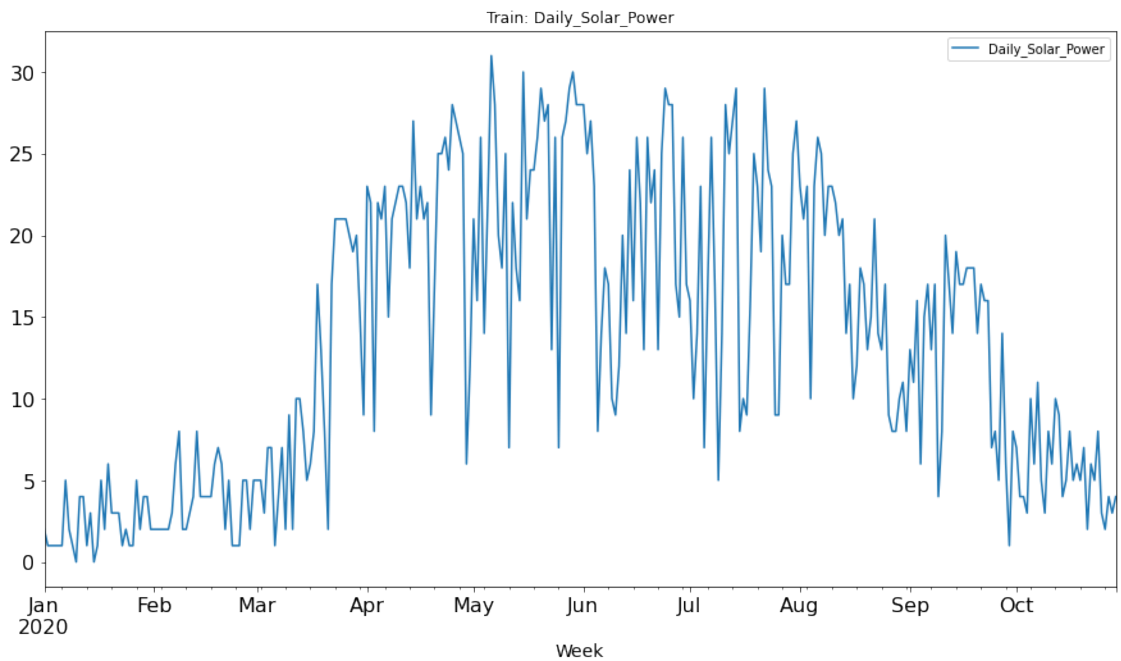
[19]:
```
train=df[0:-12]
test=df[-12:]
```

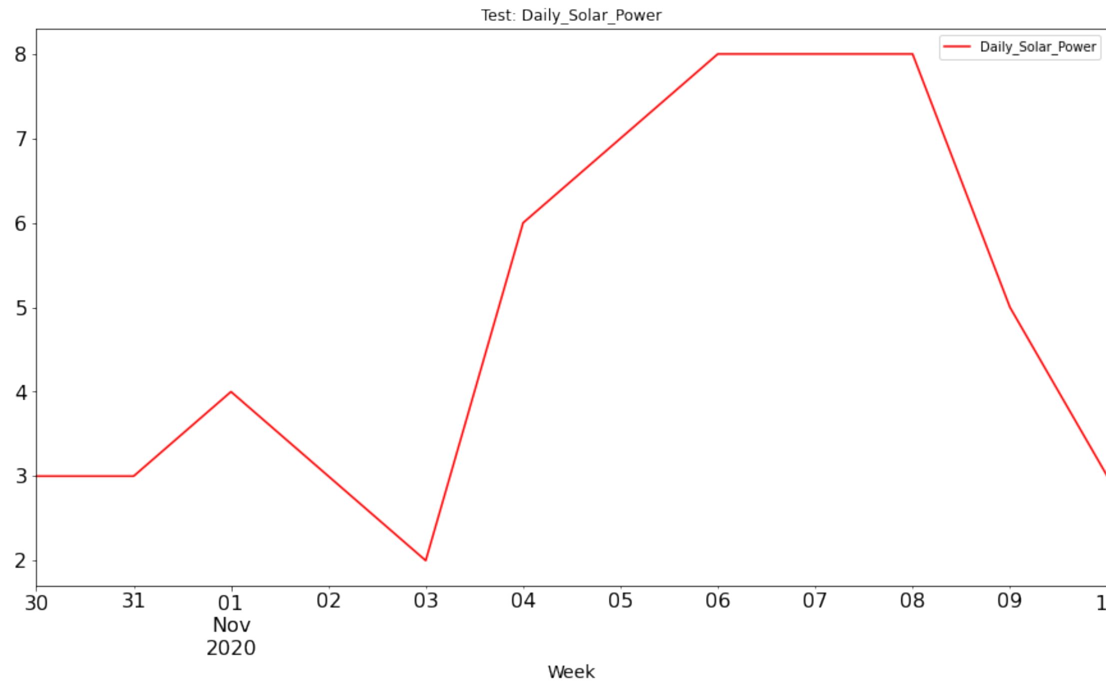
[20]:
```
print(train.shape) #print the shape of train set
print(test.shape) #print the shape of test set
```

```
(303, 1)
(12, 1)
```

Plot the Training and Test Sets

[21]:
```
#Plotting train and test data
train.plot(figsize=(15,8), title= 'Train: Daily_Solar_Power', fontsize=16)␣
↪#plot the training sets
plt.xlabel("Week", fontsize=14)
test.plot(figsize=(15,8), title= 'Test: Daily_Solar_Power', fontsize=16,␣
↪color="r") #plot the test sets
plt.xlabel("Week", fontsize=14)
plt.show() #show the plot
```

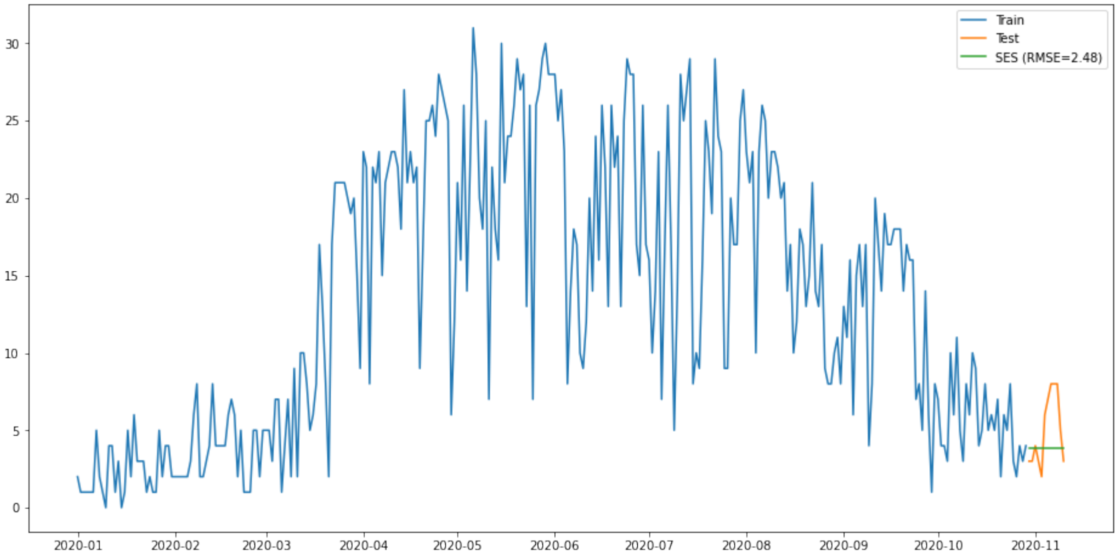




1.5.2 Simple Exponential Smoothing

[22]:
```
# Fit the model
pred = test.copy()
fit2 = SimpleExpSmoothing(np.asarray(train["Daily_Solar_Power"])).
 ↪fit(smoothing_level=0.3, optimized=False)
pred['SES'] = fit2.forecast(len(test))
# Calculate KPI's
mae = mean_absolute_error(test["Daily_Solar_Power"], pred.SES)/
 ↪test["Daily_Solar_Power"].abs().mean()
print("MAE%:", round(mae*100,1))
rmse = sqrt(mean_squared_error(test["Daily_Solar_Power"], pred.SES))
print("RMSE {:,.2f}".format(rmse))

# Plot
plt.figure(figsize=(16,8))
plt.plot(train['Daily_Solar_Power'], label='Train')
plt.plot(test['Daily_Solar_Power'], label='Test')
plt.plot(pred['SES'], label='SES (RMSE={:.2f})'.format(rmse))
plt.legend()
plt.show()
```

```
MAE%: 40.5
RMSE 2.48
```



[23]:

```
pred
```

[23]:

```
            Daily_Solar_Power   SES
date
2020-10-30               3.00 3.85
2020-10-31               3.00 3.85
2020-11-01               4.00 3.85
2020-11-02               3.00 3.85
2020-11-03               2.00 3.85
2020-11-04               6.00 3.85
2020-11-05               7.00 3.85
2020-11-06               8.00 3.85
2020-11-07               8.00 3.85
2020-11-08               8.00 3.85
2020-11-09               5.00 3.85
2020-11-10               3.00 3.85
```

Using Simple Exponential Smoothing, we are getting 2.48 of RMSE which root mean squared error.

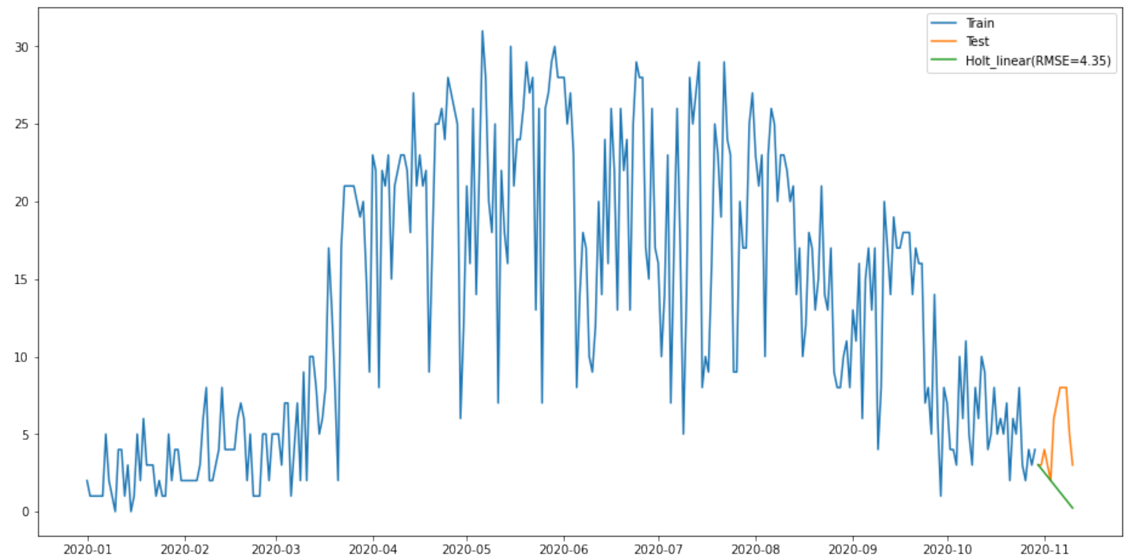
1.5.3 Double Exponential Smoothing

[24]:

```
# Fit the model
pred = test.copy()
fit1 = Holt(np.asarray(train['Daily_Solar_Power'])).fit(smoothing_level = 0.3,␣
 ↪smoothing_slope=0.2)
pred['Holt_linear'] = fit1.forecast(len(test))
# Calculate KPI
```

```
mae = mean_absolute_error(test["Daily_Solar_Power"], pred.Holt_linear)/
 ↪test["Daily_Solar_Power"].abs().mean()
print("MAE%:", round(mae*100,1))
rmse = sqrt(mean_squared_error(test["Daily_Solar_Power"], pred.Holt_linear))
print("RMSE {:,.2f}".format(rmse))

# Plot
plt.figure(figsize=(16,8))
plt.plot(train['Daily_Solar_Power'], label='Train')
plt.plot(test['Daily_Solar_Power'], label='Test')
plt.plot(pred['Holt_linear'], label='Holt_linear(RMSE={:.2f})'.format(rmse))
plt.legend()
plt.show()
```

```
MAE%: 67.6
RMSE 4.35
```



[25]:
```
pred
```

[25]:

date	Daily_Solar_Power	Holt_linear
2020-10-30	3.00	3.02
2020-10-31	3.00	2.77
2020-11-01	4.00	2.51
2020-11-02	3.00	2.26
2020-11-03	2.00	2.01
2020-11-04	6.00	1.75
2020-11-05	7.00	1.50

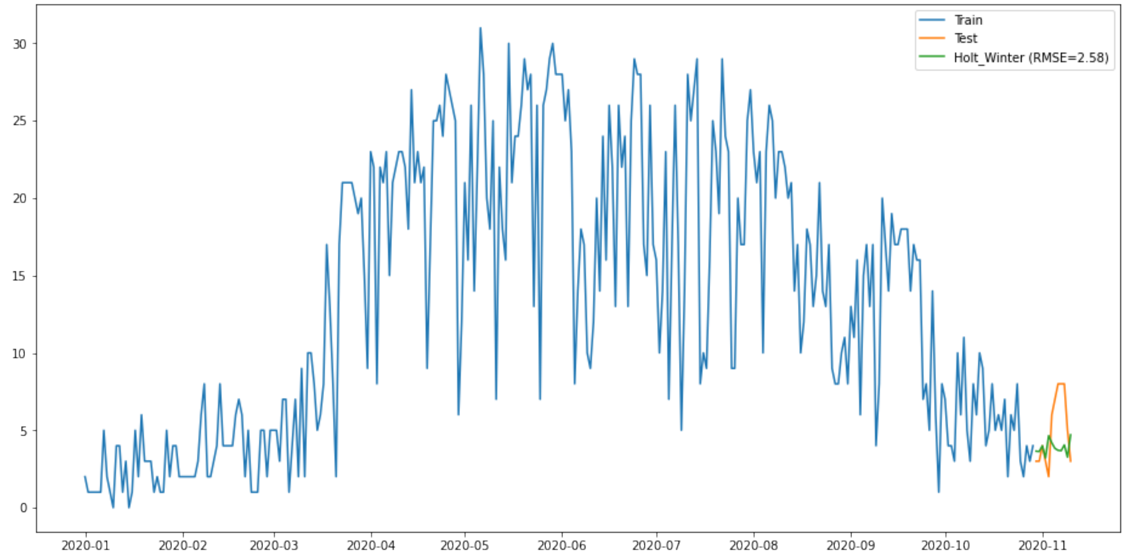
2020-11-06	8.00	1.24
2020-11-07	8.00	0.99
2020-11-08	8.00	0.73
2020-11-09	5.00	0.48
2020-11-10	3.00	0.23

Using Double Exponential Smoothing, we are getting root mean squared error of 4.35

1.5.4 Triple Exponential Smoothing (Holt Winters)

[26]:
```
# Fit the model
pred = test.copy()
fit1 = ExponentialSmoothing(np.asarray(train['Daily_Solar_Power']),␣
↪seasonal_periods=7 ,trend='add', seasonal='add').fit()

pred['Holt_Winter'] = fit1.forecast(len(test))
# Calculate KPI's
mae = mean_absolute_error(test["Daily_Solar_Power"], pred.Holt_Winter)/
↪test["Daily_Solar_Power"].abs().mean()
print("MAE%:", round(mae*100,1))
rmse = sqrt(mean_squared_error(test["Daily_Solar_Power"], pred.Holt_Winter))
print("RMSE {:,.2f}".format(rmse))

# Plot
plt.figure(figsize=(16,8))
plt.plot( train['Daily_Solar_Power'], label='Train')
plt.plot(test['Daily_Solar_Power'], label='Test')
plt.plot(pred['Holt_Winter'], label='Holt_Winter (RMSE={:.2f})'.format(rmse))

plt.legend()
plt.show()
```

```
MAE%: 41.9
RMSE 2.58
```



[27]:
```
pred
```

[27]:

date	Daily_Solar_Power	Holt_Winter
2020-10-30	3.00	3.65
2020-10-31	3.00	3.63
2020-11-01	4.00	4.00
2020-11-02	3.00	3.21
2020-11-03	2.00	4.65
2020-11-04	6.00	4.19
2020-11-05	7.00	3.83
2020-11-06	8.00	3.70
2020-11-07	8.00	3.68
2020-11-08	8.00	4.05
2020-11-09	5.00	3.26
2020-11-10	3.00	4.70

Using Triple Exponential Smoothing, we have observed root mean squared error (RMSE) of 2.58

1.5.5 Conclusion for Exponential Smoothing

Using Exponential Smoothing techniques, we are getting low error with simple and triple exponential smoothing.

1.6 Part 3: ARIMA Model

In this part, we will be using ARIMA model to forecast solar powerconsumption numbers.

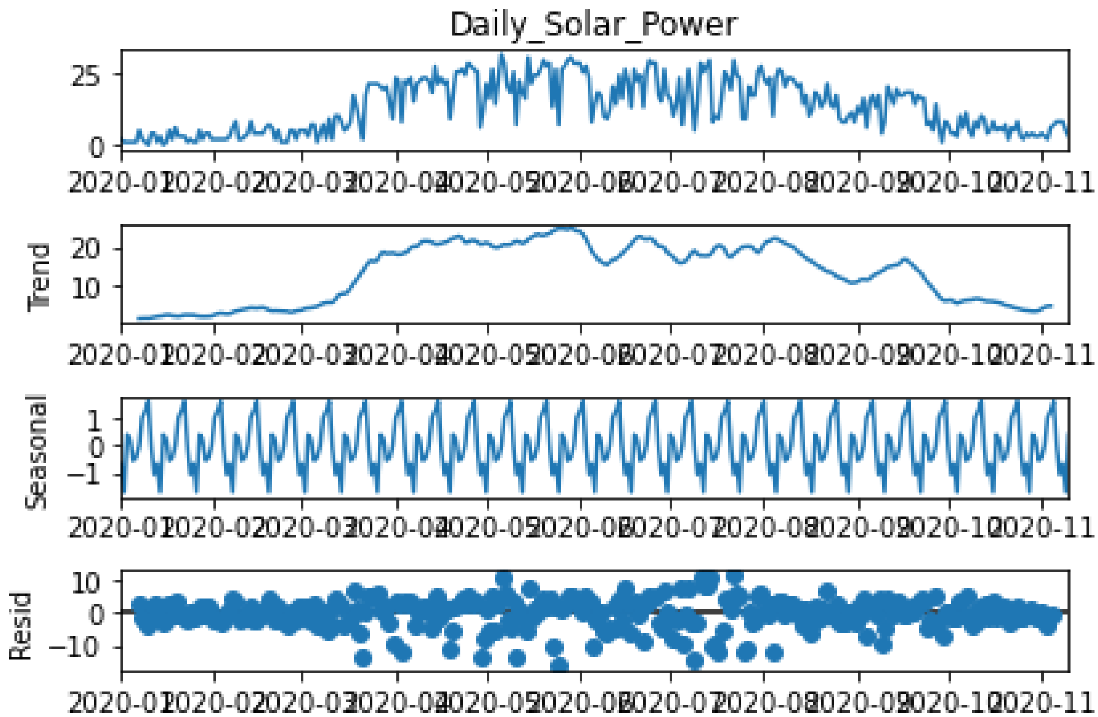
[28]:
```
df = pd.read_excel("Solar_Power_Data_Daily.xlsx", parse_dates=True, index_col␣
↪=0) #read the data into dataframe and parse the date column
pd.options.display.float_format = '{:,.2f}'.format #to display float values␣
↪properly
```

[29]:
```
df=df.drop(["Cumulative_solar_power","Daily_Electricity","Daily_Gas"],1)
df=df.filter(like='2020',axis=0)
df.head()
```

[29]:

	Daily_Solar_Power
date	
2020-01-01	2.00
2020-01-02	1.00
2020-01-03	1.00
2020-01-04	1.00
2020-01-05	1.00

[30]:
```
# Import seasonal decompose
from statsmodels.tsa.seasonal import seasonal_decompose

# Perform additive decomposition
decomp = seasonal_decompose(df['Daily_Solar_Power'],
                            freq=12)

# Plot decomposition
decomp.plot()
plt.rcParams["figure.figsize"] = (15,8)
plt.show()
```



Based on the Trend plot, Solar power production rises in the middle and then declines. Based on the Seasonal plot, there is definite seasonality in the Power Production data which causes the production to fluctuate between 1 and -1.

Check for Stationarity

[31]:
```
from statsmodels.tsa.stattools import adfuller
# Run Dicky-Fuller test
result = adfuller(df['Daily_Solar_Power'])
```

[32]:
```
# Print test statistic
print(result)
```

```
(-1.7189511159166513, 0.42137569034947636, 9, 305, {'1%': -3.451973573620699,
'5%': -2.8710633193086648, '10%': -2.5718441306100512}, 1837.4618538319874)
```

Since the ADF t-test value (-1.719) is greater than the critical value (5%), we have to make the series stationary.

[33]:
```
# Make it stationary Take the first difference of the data
df_diff = df.diff().dropna()
```

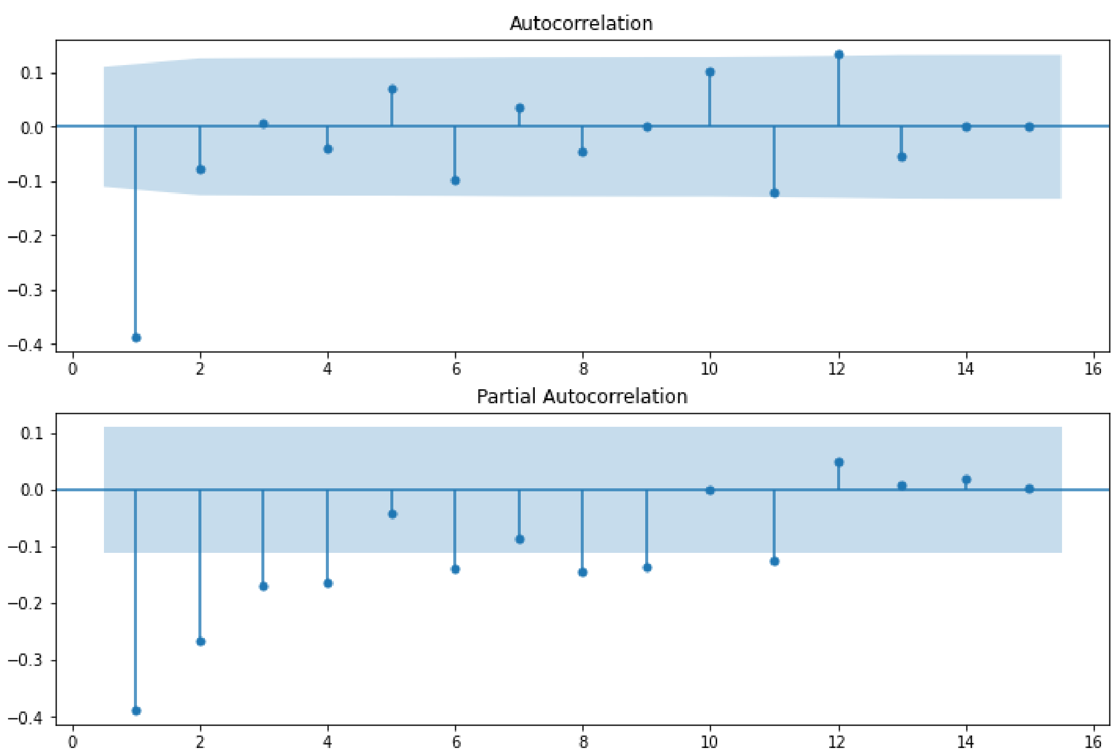
[34]:
```
# Run Dicky-Fuller test
result = adfuller(df_diff['Daily_Solar_Power'])
```

[35]:
```
# Print test statistic
print(result)
```

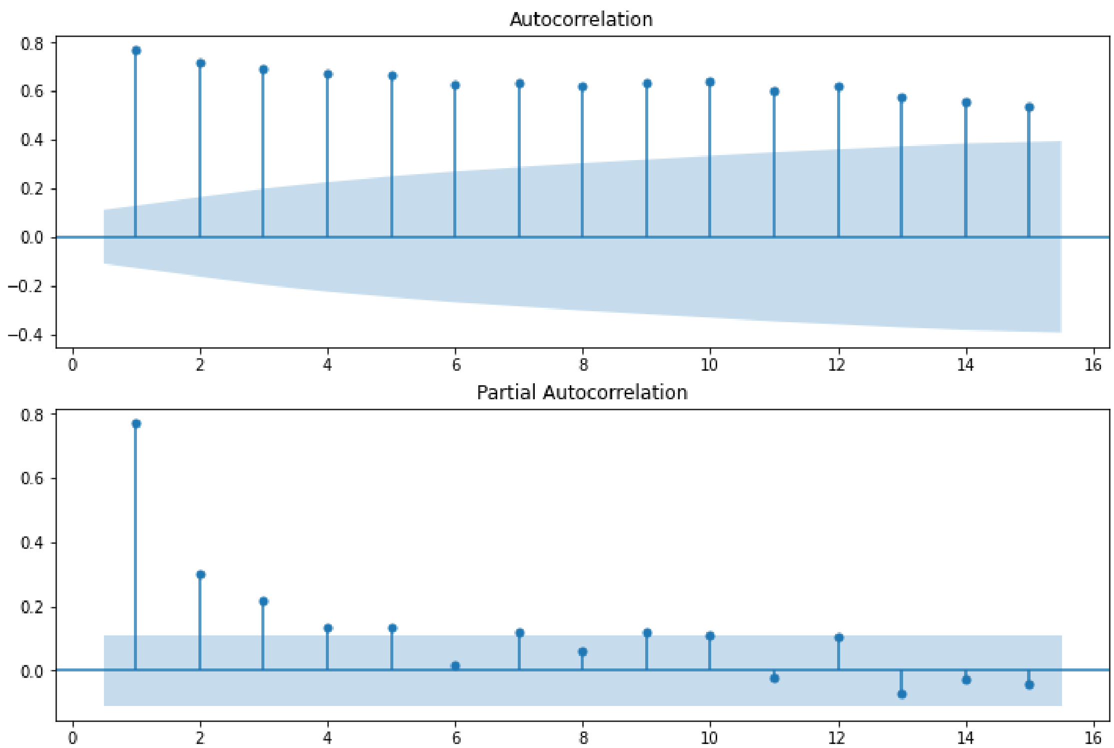
```
(-8.434960724742318, 1.8272021843510273e-13, 10, 303, {'1%':
-3.4521175397304784, '5%': -2.8711265007266666, '10%': -2.571877823851692},
1833.1273239518591)
```

Since the ADF t-test value is less than the critical value (5%), hence the series is stationary.

[36]:
```
# Import ACF and PCF functions
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Create figure
fig, (ax1, ax2) = plt.subplots(2,1, figsize=(12,8))

# Plot the ACF on ax1
plot_acf(df_diff, lags=15, zero=False, ax=ax1)

# Plot the PACF of on ax2
plot_pacf(df_diff, lags=15, zero=False, ax=ax2)

plt.show()
```



[37]:
```
# Create figure
fig, (ax1, ax2) = plt.subplots(2,1, figsize=(12,8))

# Plot the ACF on ax1
plot_acf(df, lags=15, zero=False, ax=ax1)

# Plot the PACF of on ax2
plot_pacf(df, lags=15, zero=False, ax=ax2)

plt.show()
```



Use the grid search method to calculate the parameter p and q

[38]:
```
# Import the SARIMAX model
from statsmodels.tsa.statespace.sarimax import SARIMAX

# Create empty list to store search results
order_aic_bic=[]
# Loop over p values from 0-2
for p in range(3):
# Loop over q values from 0-2
    for q in range(3):
        try:
```

```
            # Create and fit ARIMA(p,d,q) model
            model = SARIMAX(df, order=(p,0,q), trend='c')
            results = model.fit()
            # Append order and results tuple
            order_aic_bic.append((p,q,results.aic, results.bic))
        except:
            print(p, q, None, None)
```

[39]:

```
# Construct DataFrame from order_aic_bic
order_df = pd.DataFrame(order_aic_bic,
                        columns=['p', 'q', 'AIC', 'BIC'])

# Print order_df in order of increasing AIC
print(order_df.sort_values('AIC'))

# Print order_df in order of increasing BIC
print(order_df.sort_values('BIC'))
```

```
   p  q       AIC       BIC
7  2  1 1,924.05 1,942.81
5  1  2 1,924.72 1,943.48
8  2  2 1,925.88 1,948.40
4  1  1 1,929.55 1,944.56
6  2  0 1,959.23 1,974.24
3  1  0 1,988.42 1,999.68
2  0  2 2,068.56 2,083.57
1  0  1 2,123.25 2,134.51
0  0  0 2,272.50 2,280.00
   p  q       AIC       BIC
7  2  1 1,924.05 1,942.81
5  1  2 1,924.72 1,943.48
4  1  1 1,929.55 1,944.56
8  2  2 1,925.88 1,948.40
6  2  0 1,959.23 1,974.24
3  1  0 1,988.42 1,999.68
2  0  2 2,068.56 2,083.57
1  0  1 2,123.25 2,134.51
0  0  0 2,272.50 2,280.00
```

Based on the results p=2 and q=1

[40]:

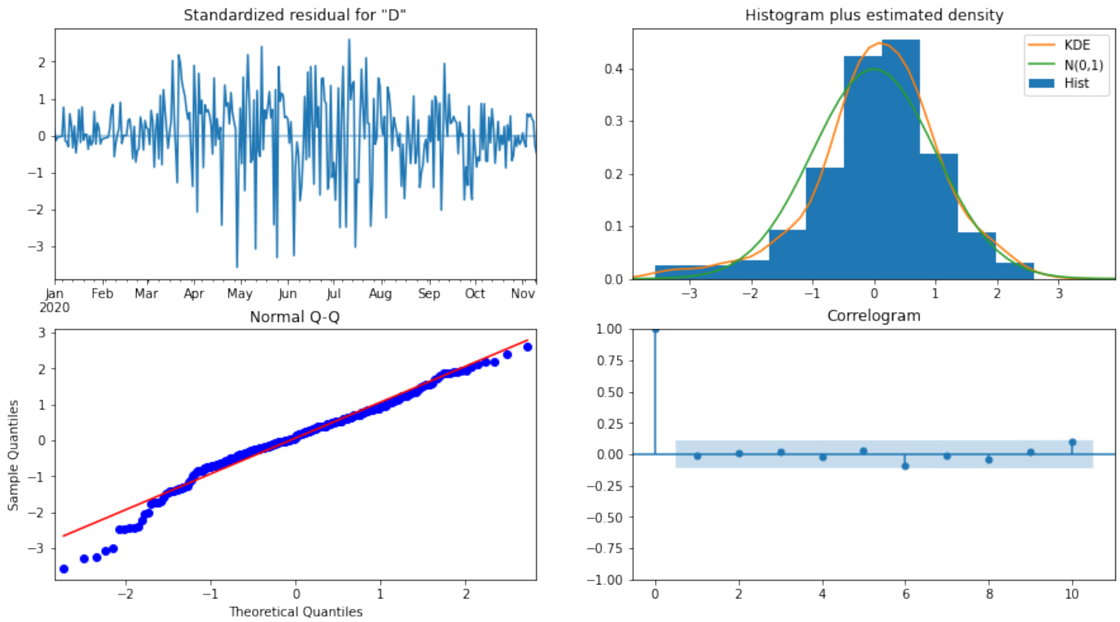
```
# Instantiate the model
arma = SARIMAX(df, order=(2,0,1))
results = arma.fit()
print(results.summary())
```

```
                               SARIMAX Results
==============================================================================
```

```
Dep. Variable:      Daily_Solar_Power   No. Observations:                  315
Model:               SARIMAX(2, 0, 1)   Log Likelihood                -957.693
Date:                Sat, 05 Jun 2021   AIC                           1923.385
Time:                        22:40:12   BIC                           1938.396
Sample:                    01-01-2020   HQIC                          1929.383
                         - 11-10-2020
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.2218      0.066     18.434      0.000       1.092       1.352
ar.L2         -0.2250      0.065     -3.441      0.001      -0.353      -0.097
ma.L1         -0.8365      0.041    -20.380      0.000      -0.917      -0.756
sigma2        25.3956      1.861     13.645      0.000      21.748      29.043
================================================================================
===
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):
41.56
Prob(Q):                              0.90   Prob(JB):
0.00
Heteroskedasticity (H):               1.14   Skew:
-0.62
Prob(H) (two-sided):                  0.50   Kurtosis:
4.28
================================================================================
===

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).
```

[41]:
```python
# Create the 4 diagostics plots
plt.figure(figsize=(10,8))
results.plot_diagnostics()
plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```



As depicted from the plots, below are the observations.

Standardized residual - There are no obvious patterns in the residuals.
Histogram plus KDE estimate - The KDE curve is similar to the normal distribution.
Normal Q-Q - Most of the data points lie around the straight line.
Correlogram - 95% of correlations for lag greater than one are not significant.

[42]:
```python
rmse = np.round(results.mse**0.5,2)
print(f"RMSE: {rmse}")
```

```
RMSE: 5.04
```

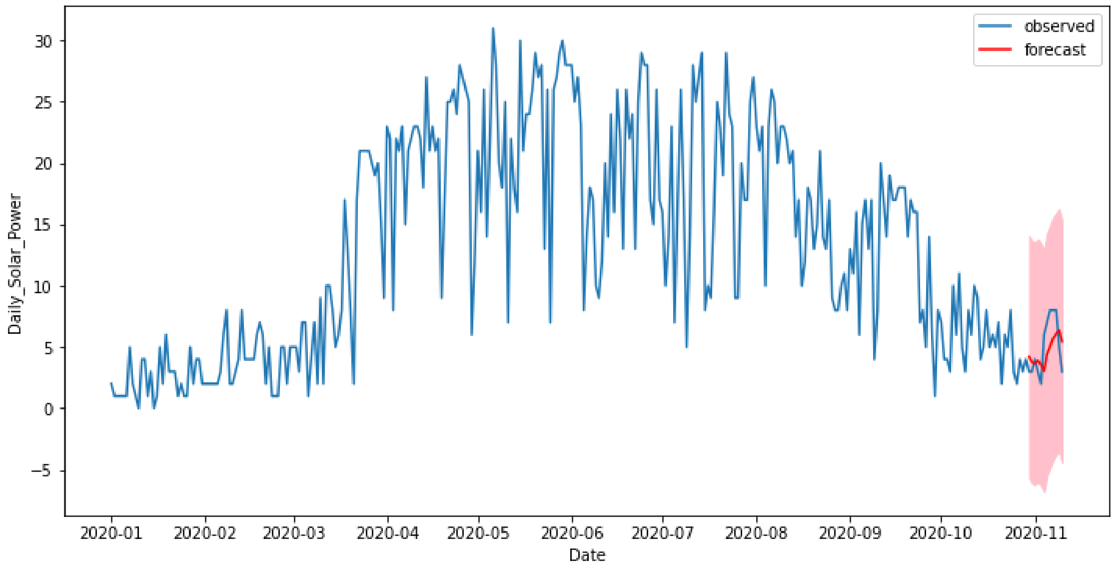
1.6.1 Generate One Step Forecast

[43]:
```python
# Generate predictions
one_step_forecast = results.get_prediction(start=-12)

# Extract prediction mean
mean_forecast = one_step_forecast.predicted_mean

# Get confidence intervals of predictions
confidence_intervals = one_step_forecast.conf_int()

confidence_intervals
# Select lower and upper confidence limits
lower_limits = confidence_intervals.loc[:,'lower Daily_Solar_Power']
upper_limits = confidence_intervals.loc[:,'upper Daily_Solar_Power']
```

```python
# Print best estimate predictions
print(mean_forecast)
```

```
2020-10-30    4.21
2020-10-31    3.78
2020-11-01    3.64
2020-11-02    3.91
2020-11-03    3.53
2020-11-04    3.05
2020-11-05    4.41
2020-11-06    5.04
2020-11-07    5.72
2020-11-08    6.07
2020-11-09    6.36
2020-11-10    5.44
Freq: D, Name: predicted_mean, dtype: float64
```

[44]:
```python
# plot the  data
plt.figure(figsize=(12,6))
plt.plot(df.index, df, label='observed')

# plot your mean predictions
plt.plot(mean_forecast.index, mean_forecast, color='r', label='forecast')


# shade the area between your confidence limits
plt.fill_between(lower_limits.index, lower_limits,
               upper_limits, color='pink')

# set labels, legends and show plot
plt.xlabel('Date')
plt.ylabel('Daily_Solar_Power')
plt.legend()
plt.show()
```



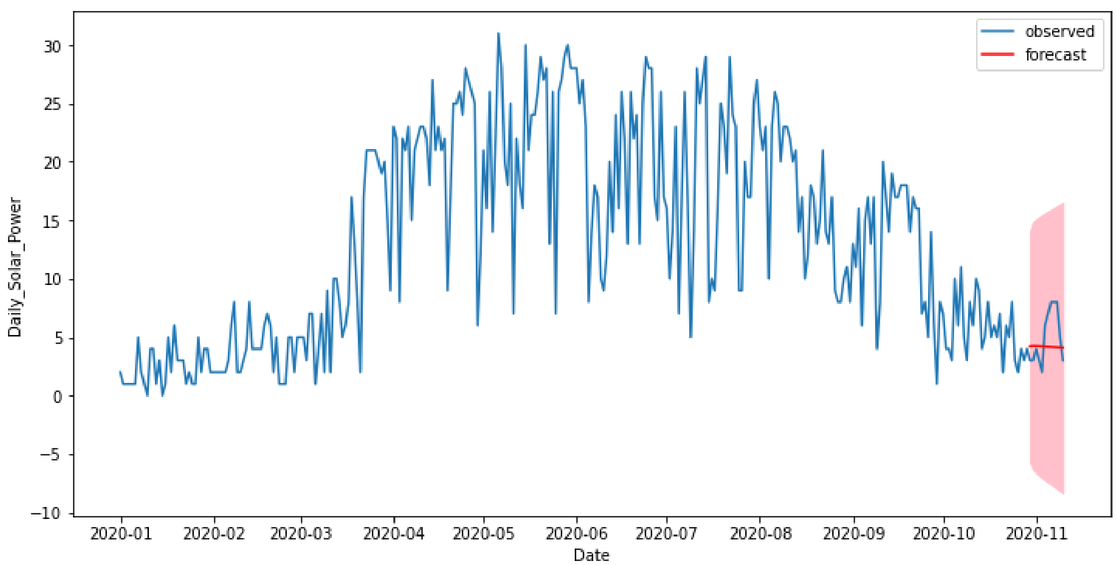
1.6.2 Generate Dynamic Predictions

[45]:
```python
# Generate predictions
one_step_forecast = results.get_prediction(start=-12, dynamic = True)

# Extract prediction mean
mean_forecast = one_step_forecast.predicted_mean

# Get confidence intervals of predictions
confidence_intervals = one_step_forecast.conf_int()

confidence_intervals
# Select lower and upper confidence limits
lower_limits = confidence_intervals.loc[:,'lower Daily_Solar_Power']
upper_limits = confidence_intervals.loc[:,'upper Daily_Solar_Power']

# Print best estimate predictions
print(mean_forecast)
```

```
2020-10-30    4.21
2020-10-31    4.24
2020-11-01    4.23
2020-11-02    4.22
2020-11-03    4.20
2020-11-04    4.19
2020-11-05    4.17
2020-11-06    4.15
2020-11-07    4.13
```

```
2020-11-08    4.12
2020-11-09    4.10
2020-11-10    4.08
Freq: D, Name: predicted_mean, dtype: float64
```

[46]:
```python
# plot the  data
plt.figure(figsize=(12,6))
plt.plot(df.index, df, label='observed')

# plot your mean predictions
plt.plot(mean_forecast.index, mean_forecast, color='r', label='forecast')

# shade the area between your confidence limits
plt.fill_between(lower_limits.index, lower_limits,
                upper_limits, color='pink')

# set labels, legends and show plot
plt.xlabel('Date')
plt.ylabel('Daily_Solar_Power')
plt.legend()
plt.show()
```



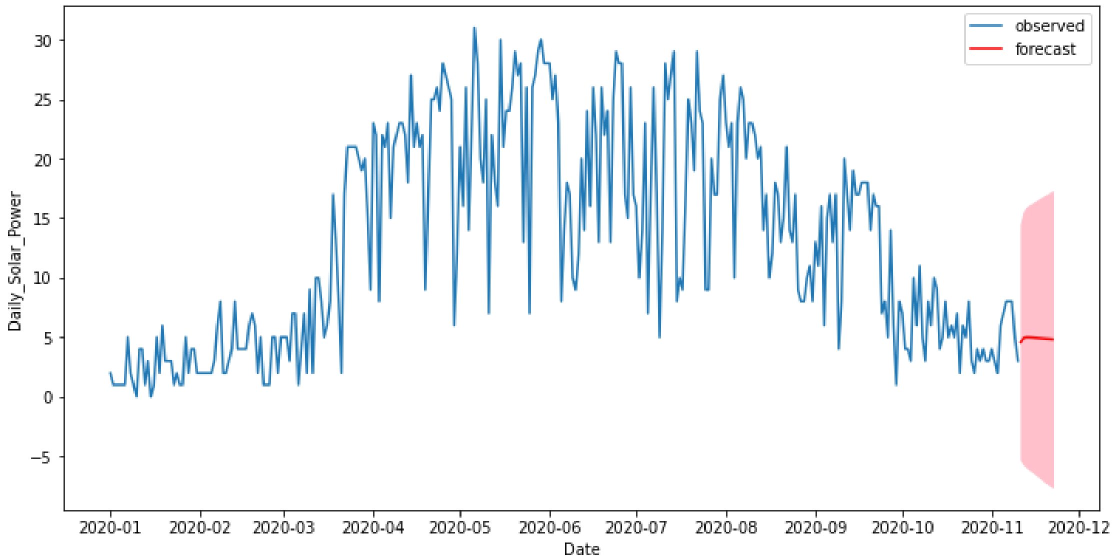
1.6.3 Out of the Sample Predictions

[47]:
```python
forecast = results.get_forecast(steps =12)
mean_forecast= forecast.predicted_mean
confidence_intervals= forecast.conf_int()
confidence_intervals
```

```python
# Select lower and upper confidence limits
lower_limits = confidence_intervals.loc[:,'lower Daily_Solar_Power']
upper_limits = confidence_intervals.loc[:,'upper Daily_Solar_Power']

# Print best estimate predictions
print(mean_forecast)
```

```
2020-11-11    4.59
2020-11-12    4.93
2020-11-13    4.99
2020-11-14    4.99
2020-11-15    4.97
2020-11-16    4.95
2020-11-17    4.93
2020-11-18    4.91
2020-11-19    4.89
2020-11-20    4.87
2020-11-21    4.85
2020-11-22    4.83
Freq: D, Name: predicted_mean, dtype: float64
```

[48]:
```python
# plot the  data
plt.figure(figsize=(12,6))
plt.plot(df.index, df, label='observed')

# plot your mean predictions
plt.plot(mean_forecast.index, mean_forecast, color='r', label='forecast')

# shade the area between your confidence limits
plt.fill_between(lower_limits.index, lower_limits,
               upper_limits, color='pink')

# set labels, legends and show plot
plt.xlabel('Date')
plt.ylabel('Daily_Solar_Power')
plt.legend()
plt.show()
```



1.6.4 Conclusion for ARIMA

Using SARIMAX method, we are getting optimum results where our observed and forecasted values are almost overlapping with each other. We have observed deviation of 5.04 in the form of root mean squared error (RMSE). As shown in the plot, we have the best results in case of One Step Forecast where the forecasted and actual values are almost overlapping with each other.

1.7 Part 4: Machine Learning

[49]:
```
import pandas as pd #For Dataframe manipulation
import numpy as np #For numerical operations

import matplotlib.pyplot as plt #For plotting and visualization
import seaborn as sns #For plotting and visualization

import tensorflow as tf #For neural network architecture
import keras #for neural network architecture
from keras import Sequential #For sequential layer

#Below line is for various layers of neural network architecture
from keras.layers import Conv2D, MaxPooling2D, Dropout, BatchNormalization,␣
↪Flatten, Dense, LSTM
from keras.optimizers import SGD, RMSprop, Adam #For different optimizers
import sklearn.metrics as metrics
from keras.regularizers import l1, l2 #To add penalty as regularizer
from keras.callbacks import EarlyStopping #For Early Stopping the model before␣
↪running the specified number of epochs
```

```
import os #Module to interact with operating system

import math
import random
import datetime as dt
from statsmodels.tools.eval_measures import rmse
from keras.preprocessing.sequence import TimeseriesGenerator
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from keras.wrappers.scikit_learn import KerasRegressor
from sklearn.model_selection import GridSearchCV

#To ignore warnings
from warnings import filterwarnings
filterwarnings("ignore")
```

Read the dataset

[50]:
```
power = pd.read_excel("Solar_Power_Data_Daily.xlsx", parse_dates=True,␣
↪index_col=0)
```

[51]:
```
power.head()
```

[51]:
```
            Cumulative_solar_power  Daily_Solar_Power  Daily_Electricity  \
date
2011-10-26                    0.10               0.10              15.10
2011-10-27                   10.20              10.10               7.40
2011-10-28                   20.20              10.00               5.80
2011-10-29                   29.60               9.40               4.90
2011-10-30                   34.20               4.60              11.70

            Daily_Gas
date
2011-10-26       9.00
2011-10-27       9.20
2011-10-28       8.00
2011-10-29       6.60
2011-10-30       5.30
```

[52]:
```
power.drop(['Cumulative_solar_power','Daily_Electricity','Daily_Gas'], axis=1,␣
↪inplace=True)
```

[53]:
```
power.head()
```

[53]:
```
            Daily_Solar_Power
date
```

```
2011-10-26              0.10
2011-10-27             10.10
2011-10-28             10.00
2011-10-29              9.40
2011-10-30              4.60
```

[54]:
```python
power.shape
```

[54]:
```
(3304, 1)
```

[55]:
```python
power.info()
```

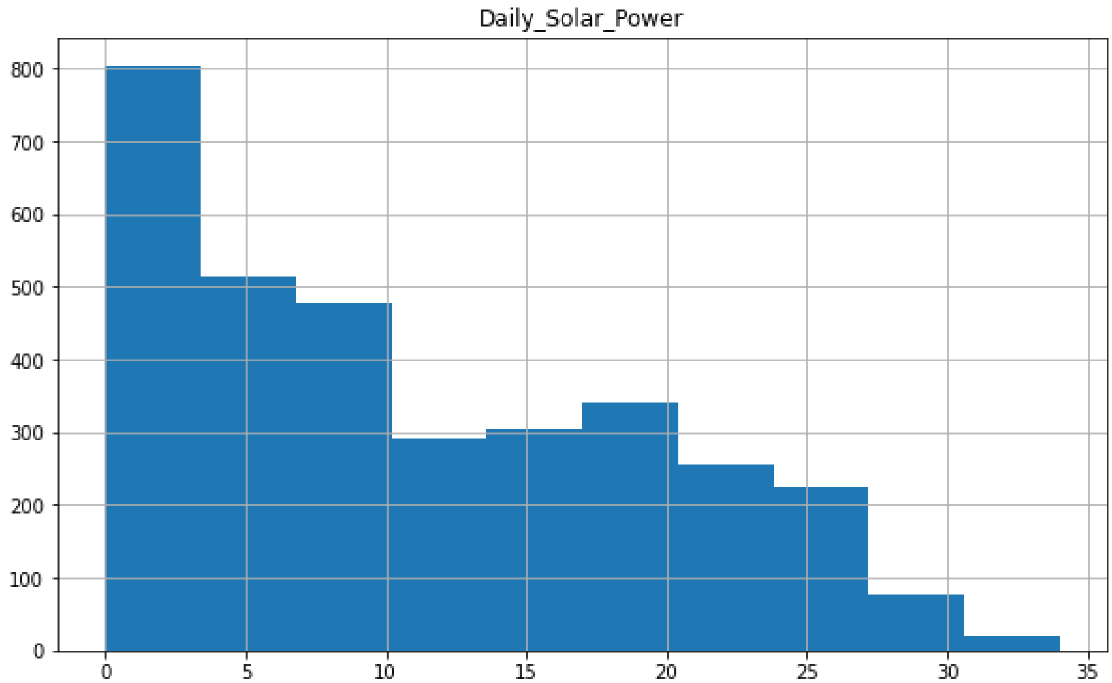
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3304 entries, 2011-10-26 to 2020-11-10
Data columns (total 1 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Daily_Solar_Power  3304 non-null   float64
dtypes: float64(1)
memory usage: 51.6 KB
```

[56]:
```python
power.describe(include="all")
```

[56]:

	Daily_Solar_Power
count	3,304.00
mean	11.04
std	8.29
min	0.00
25%	4.00
50%	9.00
75%	17.00
max	34.00

[57]:
```python
power.hist(figsize=(10,6))
plt.show()
```



Prepare the Dataset for Machine Learning

[58]:
```
# reframe as supervised learning
# lab observation (t-1) is the input variable and t is the output variable.
df = pd.DataFrame()
print(df)
```

```
Empty DataFrame
Columns: []
Index: []
```

[59]:
```
# Create 7 days of lag values to predict current observation
# Shift of 7 days in this case
for i in range(7,0,-1):
    df[['t-'+str(i)]] = power.shift(i)
print(df)
```

```
            t-7  t-6  t-5  t-4   t-3   t-2   t-1
date
2011-10-26  NaN  NaN  NaN  NaN   NaN   NaN   NaN
2011-10-27  NaN  NaN  NaN  NaN   NaN   NaN  0.10
2011-10-28  NaN  NaN  NaN  NaN   NaN  0.10 10.10
2011-10-29  NaN  NaN  NaN  NaN  0.10 10.10 10.00
2011-10-30  NaN  NaN  NaN 0.10 10.10 10.00  9.40
…          …   …   …   …    …    …    …
```

```
2020-11-06 3.00 3.00 4.00 3.00  2.00  6.00  7.00
2020-11-07 3.00 4.00 3.00 2.00  6.00  7.00  8.00
2020-11-08 4.00 3.00 2.00 6.00  7.00  8.00  8.00
2020-11-09 3.00 2.00 6.00 7.00  8.00  8.00  8.00
2020-11-10 2.00 6.00 7.00 8.00  8.00  8.00  5.00

[3304 rows x 7 columns]
```

[60]:
```
# Create column t (original column)
df['t'] = power.values
print(df.head(8))
```

```
            t-7   t-6   t-5   t-4   t-3   t-2   t-1     t
date
2011-10-26  NaN   NaN   NaN   NaN   NaN   NaN   NaN  0.10
2011-10-27  NaN   NaN   NaN   NaN   NaN   NaN  0.10 10.10
2011-10-28  NaN   NaN   NaN   NaN   NaN  0.10 10.10 10.00
2011-10-29  NaN   NaN   NaN   NaN  0.10 10.10 10.00  9.40
2011-10-30  NaN   NaN   NaN  0.10 10.10 10.00  9.40  4.60
2011-10-31  NaN   NaN  0.10 10.10 10.00  9.40  4.60  3.80
2011-11-01  NaN  0.10 10.10 10.00  9.40  4.60  3.80  8.60
2011-11-02 0.10 10.10 10.00  9.40  4.60  3.80  8.60  5.00
```

[61]:
```
# Create a new subsetted dataframe, removing Nans from first 7 rows
df_power = df[7:]
print(df_power)
```

```
             t-7   t-6   t-5  t-4  t-3  t-2  t-1    t
date
2011-11-02  0.10 10.10 10.00 9.40 4.60 3.80 8.60 5.00
2011-11-03 10.10 10.00  9.40 4.60 3.80 8.60 5.00 7.00
2011-11-04 10.00  9.40  4.60 3.80 8.60 5.00 7.00 1.90
2011-11-05  9.40  4.60  3.80 8.60 5.00 7.00 1.90 5.20
2011-11-06  4.60  3.80  8.60 5.00 7.00 1.90 5.20 6.10
…           …     …     …    …    …    …    …    …
2020-11-06  3.00  3.00  4.00 3.00 2.00 6.00 7.00 8.00
2020-11-07  3.00  4.00  3.00 2.00 6.00 7.00 8.00 8.00
2020-11-08  4.00  3.00  2.00 6.00 7.00 8.00 8.00 8.00
2020-11-09  3.00  2.00  6.00 7.00 8.00 8.00 8.00 5.00
2020-11-10  2.00  6.00  7.00 8.00 8.00 8.00 5.00 3.00

[3297 rows x 8 columns]
```

[62]:
```
df_power.shape
```

[62]: (3297, 8)

[63]:
```
# Split Data into dependent(target) and independent(features) variables

power = df_power.values
# Lagged variables (features) and original time series data (target)
X2= power[:,0:-1]  # slice all rows and start with column 0 and go up to but␣
↪not including the last column
y2 = power[:,-1]  # slice all rows and last column, essentially separating out␣
↪'t' column
```

[64]:
```
# Columns t-1 to t-7, which are the lagged variables
X2.shape
```

[64]: (3297, 7)

[65]:
```
# Column t, which is the original time series
# Give first 7 values of target variable, time series
y2.shape
```

[65]: (3297,)

Model Building with 85-15 split of dataset into training and test sets

[66]:
```
# Target(Y) Train-Test split

Y2 = y2
traintarget_size = int(len(Y2) * 0.85)   # Set split
print(traintarget_size)
train_target, test_target = Y2[:traintarget_size], Y2[traintarget_size:len(Y2)]

print('Observations for Target: %d' % (len(Y2)))
print('Training Observations for Target: %d' % (len(train_target)))
print('Testing Observations for Target: %d' % (len(test_target)))
```

```
2802
Observations for Target: 3297
Training Observations for Target: 2802
Testing Observations for Target: 495
```

[67]:
```
# Features(X) Train-Test split

trainfeature_size = int(len(X2) * 0.85)
train_feature, test_feature = X2[:trainfeature_size], X2[trainfeature_size:
↪len(X2)]
print('Observations for feature: %d' % (len(X2)))
print('Training Observations for feature: %d' % (len(train_feature)))
print('Testing Observations for feature: %d' % (len(test_feature)))
```

```
Observations for feature: 3297
```

```
Training Observations for feature: 2802
Testing Observations for feature: 495
```

[68]:
```
train_feature
```

[68]:
```
array([[ 0.1, 10.1, 10. , …,  4.6,  3.8,  8.6],
       [10.1, 10. ,  9.4, …,  3.8,  8.6,  5. ],
       [10. ,  9.4,  4.6, …,  8.6,  5. ,  7. ],
       …,
       [22. , 24. , 28. , …, 29. , 29. , 27. ],
       [24. , 28. , 30. , …, 29. , 27. , 27. ],
       [28. , 30. , 29. , …, 27. , 27. , 21. ]])
```

1.7.1 Benchmark Model

[69]:
```
from sklearn.linear_model import LinearRegression

reg = LinearRegression() # Create a linear regression object

reg = reg.fit(train_feature, train_target) # Fit it to the training data

# Create two predictions for the training and test sets
train_prediction = reg.predict(train_feature)
test_prediction = reg.predict(test_feature)
```

[70]:
```
# Compute the MAE for both the training and test sets

MAE_train=np.mean(abs(train_target-train_prediction))/np.mean(test_target)
print("Tree on train set MAE%:", round(MAE_train*100,1))

MAE_test=np.mean(abs(test_target-test_prediction))/np.mean(test_target)
print("Tree on test set MAE%:", round(MAE_test*100,1))

rmse_train = np.mean((train_target - train_prediction)**2)**.5
rmse_test = np.mean((test_target - test_prediction)**2)**.5

print(f"RMSE on Train: {rmse_train:.2f}")
print(f"RMSE on Test: {rmse_test:.2f}")
```

```
Tree on train set MAE%: 30.9
Tree on test set MAE%: 29.7
RMSE on Train: 4.85
RMSE on Test: 4.74
```

1.7.2 Decision Tree Model

[71]:
```
# Decision Tree Regression Model

from sklearn.tree import DecisionTreeRegressor

# Create a decision tree regression model with default arguments
decision_tree_power = DecisionTreeRegressor()  # max_depth not set

# Fit the model to the training features and targets
decision_tree_power.fit(train_feature, train_target)

# Check the score on train and test
print(decision_tree_power.score(train_feature, train_target))
print(decision_tree_power.score(test_feature,test_target))  # predictions are␣
↪horrible if negative value, no relationship if 0
```

```
1.0
0.37756502851289786
```

[72]:
```
# Find Best Max Depth

# Loop through a few different max depths and check the performance
# Try different max depths. We want to optimize our ML models to make the best␣
↪predictions possible.
# For regular decision trees, max_depth, which is a hyperparameter, limits the␣
↪number of splits in a tree.
# You can find the best value of max_depth based on the R-squared score of the␣
↪model on the test set.

for d in [2,3,4,5,6,7,8,9,10]:
    # Create the tree and fit it
    decision_tree_power = DecisionTreeRegressor(max_depth=d)
    decision_tree_power.fit(train_feature, train_target)

    # Print out the scores on train and test
    print('max_depth=', str(d))
    print(decision_tree_power.score(train_feature, train_target))
    print(decision_tree_power.score(test_feature, test_target), '\n')  # You␣
↪want the test score to be positive

# R-square for train and test scores are below.
```

```
max_depth= 2
0.5857556529425928
0.6196341379505945

max_depth= 3
```

```
0.6273279800321974
0.6538713859477554

max_depth= 4
0.6572877430961899
0.6787155883581543

max_depth= 5
0.680751826145779
0.6841182782127145

max_depth= 6
0.7076502972711062
0.6634224601110633

max_depth= 7
0.7370653450282576
0.6544458773035877

max_depth= 8
0.7717113592690891
0.5934859099527531

max_depth= 9
0.7982950202407693
0.5721359476025982

max_depth= 10
0.8296723186457737
0.5535465824405665
```

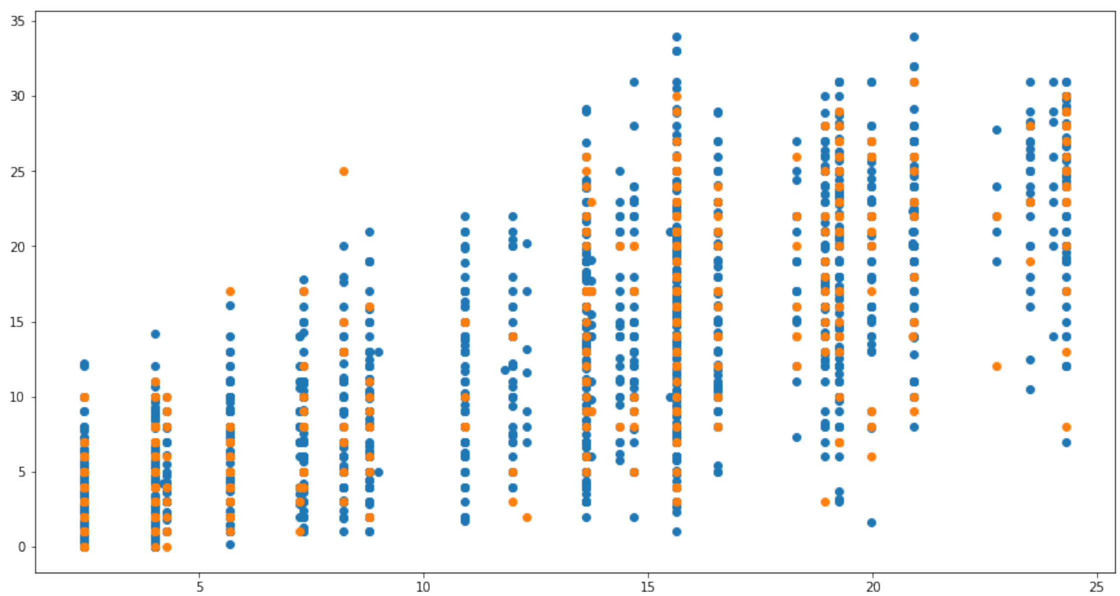
The best max_depth is max_depth that gives the best test score (positive and high).

For max depth=5, we are getting highest accuracy on the test set.

[73]:
```python
# Plot predicted against actual values

from matplotlib import pyplot as plt

# Use the best max_depth
decision_tree_power = DecisionTreeRegressor(max_depth=5) # Fill in best max␣
↪depth score here
decision_tree_power.fit(train_feature, train_target)

# Predict values for train and test
train_prediction = decision_tree_power.predict(train_feature)
```

```python
MAE_train=np.mean(abs(train_target-train_prediction))/np.mean(test_target)
print("Tree on train set MAE%:", round(MAE_train*100,1))


test_prediction = decision_tree_power.predict(test_feature)

MAE_test=np.mean(abs(test_target-test_prediction))/np.mean(test_target)
print("Tree on test set MAE%:", round(MAE_test*100,1))

rmse_train = np.mean((train_target - train_prediction)**2)**.5
rmse_test = np.mean((test_target - test_prediction)**2)**.5

print(f"RMSE on Train: {rmse_train:.2f}")
print(f"RMSE on Test: {rmse_test:.2f}")

# Scatter the predictions vs actual values, orange is predicted
plt.scatter(train_prediction, train_target, label='train')  # blue
plt.scatter(test_prediction, test_target, label='test')
plt.show()
```

```
Tree on train set MAE%: 29.9
Tree on test set MAE%: 30.6
RMSE on Train: 4.66
RMSE on Test: 4.80
```



For training set, we have 29.9% of MAE whereas for test set, we have 30.6% of MAE.

1.7.3 Random Forest Model

[74]:
```
# Random Forest Model
from sklearn.ensemble import RandomForestRegressor

# Create the random forest model and fit to the training data
rfr = RandomForestRegressor(n_estimators=200, random_state=6)
rfr.fit(train_feature, train_target)

# Look at the R^2 scores on train and test
print(rfr.score(train_feature, train_target))
print(rfr.score(test_feature, test_target))  # Try to attain a positive value
```

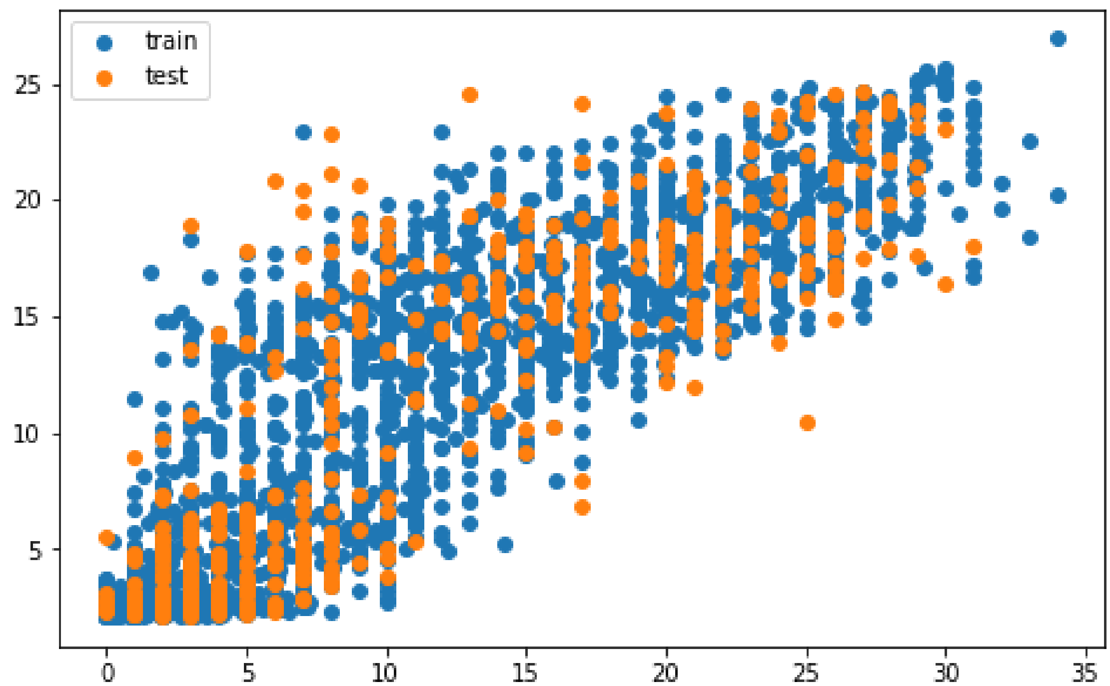
```
0.9520425974100746
0.6884022561521859
```

[75]:
```
from sklearn.model_selection import ParameterGrid
import numpy as np

# Create a dictionary of hyperparameters to search
# n_estimators is the number of trees in the forest. The larger the better, but␣
↪also takes longer it will take to compute.
# Run grid search
#grid = {'n_estimators': [200], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],␣
↪'max_features': [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12], 'random_state': [13]}
grid = {'n_estimators': [50, 100, 200, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8,␣
↪9, 10], 'max_features': [2,3,4],
        'random_state': [6]}
test_scores = []

# Loop through the parameter grid, set the hyperparameters, and save the scores
for g in ParameterGrid(grid):
    rfr.set_params(**g)  # ** is "unpacking" the dictionary
    rfr.fit(train_feature, train_target)
    test_scores.append(rfr.score(test_feature, test_target))

# Find best hyperparameters from the test score and print
best_idx = np.argmax(test_scores)
print(test_scores[best_idx], ParameterGrid(grid)[best_idx])

# The best test score
```

```
0.7098498918647175 {'random_state': 6, 'n_estimators': 100, 'max_features': 3,
'max_depth': 7}
```

[76]:
```
# Use the best hyperparameters from before to fit a random forest model
rfr = RandomForestRegressor(n_estimators=100, max_depth=7, max_features = 3,␣
↪random_state=6)
```

```
rfr.fit(train_feature, train_target)

# Make predictions with our model
train_prediction = rfr.predict(train_feature)
test_prediction = rfr.predict(test_feature)

# Create a scatter plot with train and test actual vs predictions
plt.figure(figsize=(8,5))
plt.scatter(train_target, train_prediction, label='train')
plt.scatter(test_target, test_prediction, label='test')
plt.legend()
plt.show()
```



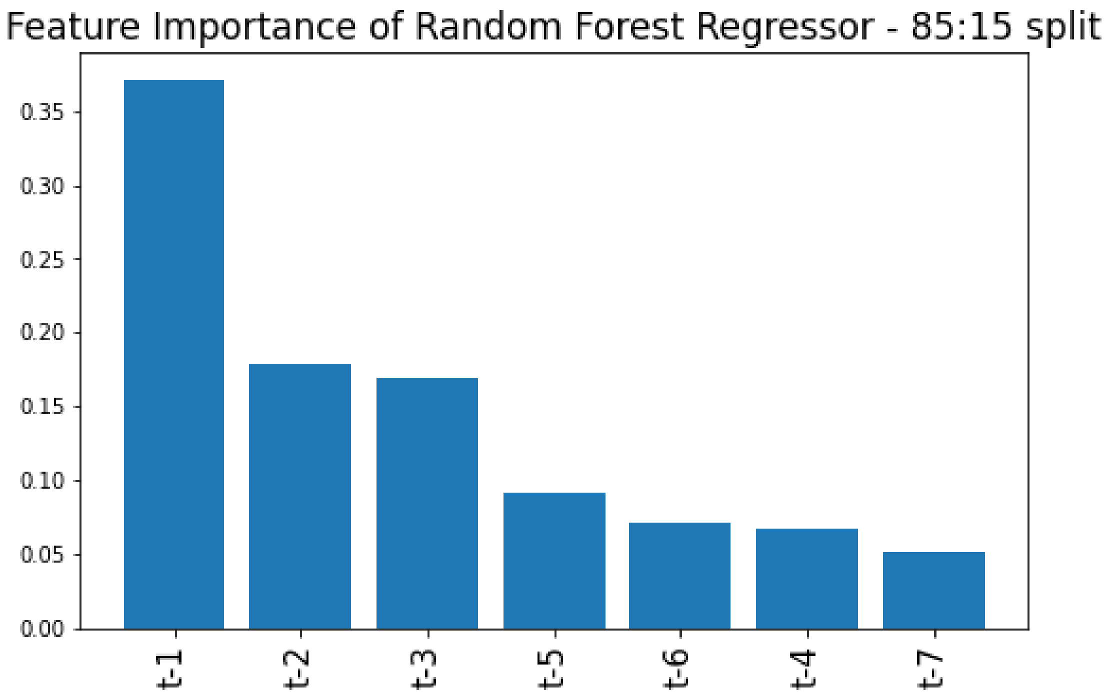
[77]:
```
# Compute the MAE for both the training and test sets

MAE_train=np.mean(abs(train_target-train_prediction))/np.mean(test_target)
print("Tree on train set MAE%:", round(MAE_train*100,1))

MAE_test=np.mean(abs(test_target-test_prediction))/np.mean(test_target)
print("Tree on test set MAE%:", round(MAE_test*100,1))

rmse_train = np.mean((train_target - train_prediction)**2)**.5
rmse_test = np.mean((test_target - test_prediction)**2)**.5
```

```
print(f"RMSE on Train: {rmse_train:.2f}")
print(f"RMSE on Test: {rmse_test:.2f}")
```

```
Tree on train set MAE%: 26.3
Tree on test set MAE%: 29.3
RMSE on Train: 4.04
RMSE on Test: 4.60
```

MAE% for training and test sets is turned out to be 26.3% and 29.3%, respectively.

[78]:
```
# Get feature importances from our random forest model
importances = rfr.feature_importances_

# Get the index of importances from greatest importance to least
sorted_index = np.argsort(importances)[::-1]
x = range(len(importances))

# Create tick labels
feature_names = ['t-7','t-6','t-5','t-4','t-3','t-2','t-1']
labels = np.array(feature_names)[sorted_index]
plt.figure(figsize=(8,5))
plt.bar(x, importances[sorted_index], tick_label=labels)

# Rotate tick labels to vertical
plt.xticks(rotation=90, size=15)
plt.title("Feature Importance of Random Forest Regressor - 85:15 split",␣
 ↪size=17)
plt.show()
```



Here, we can see how much each lag variable gives in explanatory power. It shows the explanatory power for each lag in sorted order.

In our case, t-1 is contributing most to the prediction of the dependent variable.

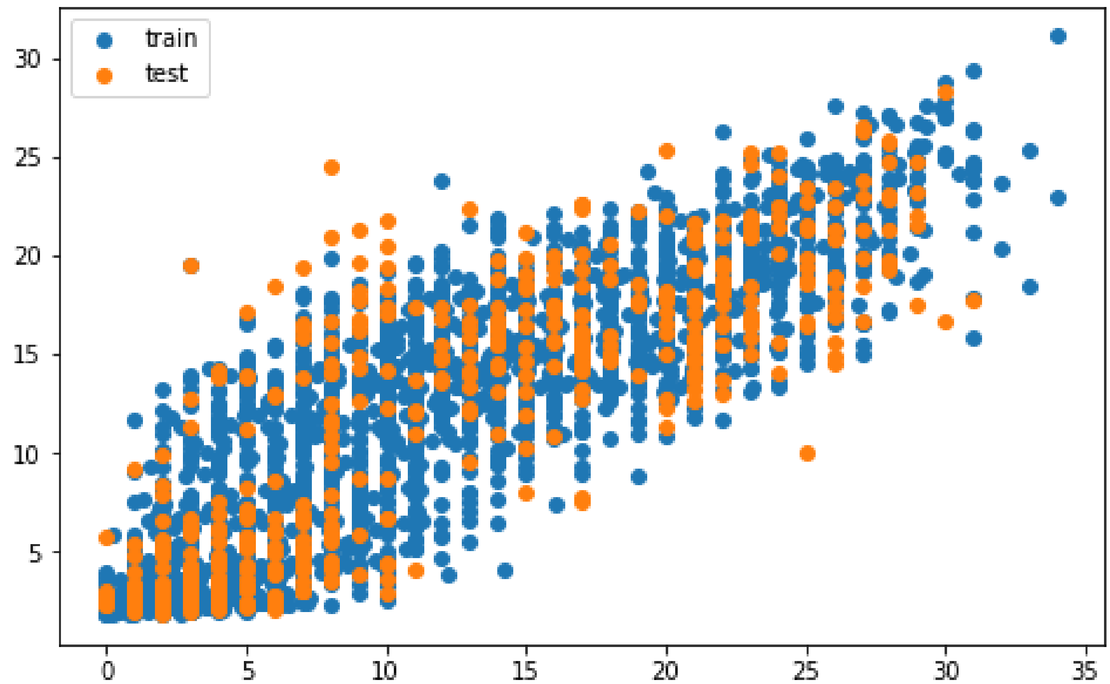
1.7.4 Gradient Boosting Tree Model

[79]:
```
from sklearn.ensemble import GradientBoostingRegressor

# Choosing subsample < 1.0 leads to a reduction of variance and an increase in␣
↪bias.
# Create GB model -- hyperparameters
gbr = GradientBoostingRegressor(max_features=7,
                                learning_rate=0.008,
                                n_estimators=2500,
                                subsample=0.8,
                                random_state=6)

gbr.fit(train_feature, train_target)

print(gbr.score(train_feature, train_target))
print(gbr.score(test_feature, test_target))
```

```
0.7865121749664066
0.7081934946150208
```

[80]:

```
# Make predictions with our model
train_prediction = gbr.predict(train_feature)
test_prediction = gbr.predict(test_feature)

# Create a scatter plot with train and test actual vs predictions
plt.figure(figsize=(8,5))
plt.scatter(train_target, train_prediction, label='train')
plt.scatter(test_target, test_prediction, label='test')
plt.legend()
plt.show()
```

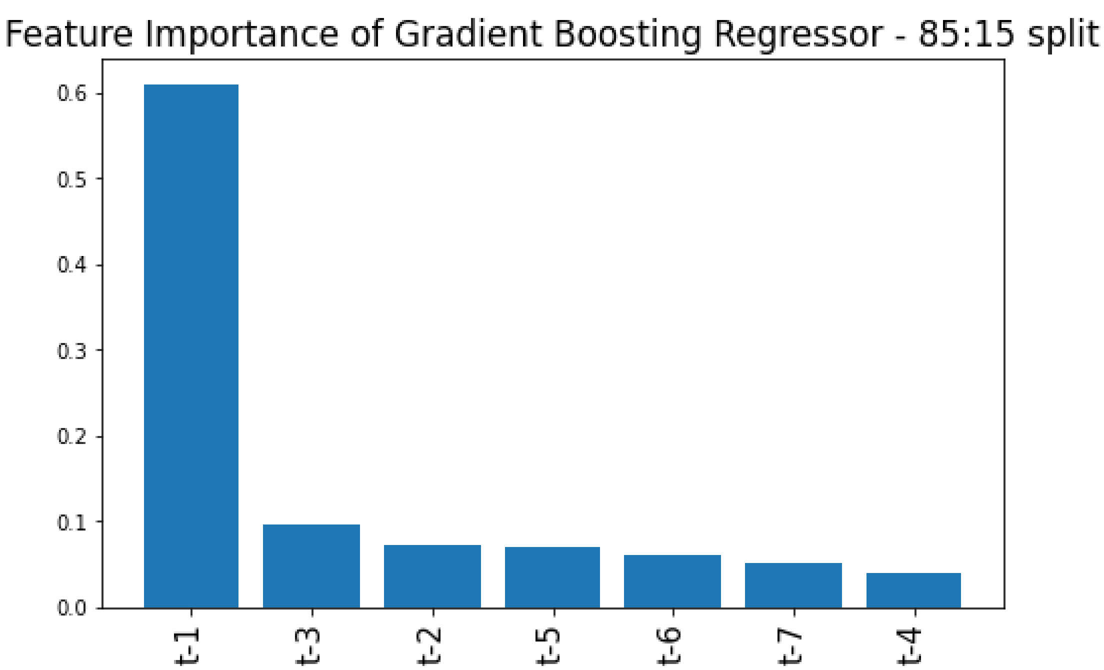


[81]:

```
# Compute the MAE for both the training and test sets

MAE_train=np.mean(abs(train_target-train_prediction))/np.mean(test_target)
print("Tree on train set MAE%:", round(MAE_train*100,1))

MAE_test=np.mean(abs(test_target-test_prediction))/np.mean(test_target)
print("Tree on test set MAE%:", round(MAE_test*100,1))

rmse_train = np.mean((train_target - train_prediction)**2)**.5
rmse_test = np.mean((test_target - test_prediction)**2)**.5

print(f"RMSE on Train: {rmse_train:.2f}")
print(f"RMSE on Test: {rmse_test:.2f}")
```

```
Tree on train set MAE%: 24.9
Tree on test set MAE%: 29.3
RMSE on Train: 3.81
RMSE on Test: 4.61
```

[82]:
```
# Gradient Boosted Model Feature Importance
# Extract feature importances from the fitted gradient boosting model
feature_importances = gbr.feature_importances_

# Get the indices of the largest to smallest feature importances
sorted_index = np.argsort(feature_importances)[::-1]
x2 = range(X2.shape[1])

# Create tick labels
feature_names = ['t-7', 't-6', 't-5', 't-4', 't-3', 't-2', 't-1']
labels = np.array(feature_names)[sorted_index]
plt.figure(figsize=(8,5))
plt.bar(x2, feature_importances[sorted_index], tick_label=labels)

# Set the tick lables to be the feature names, according to the sorted␣
↪feature_idx
plt.xticks(rotation=90, size=15)
plt.title("Feature Importance of Gradient Boosting Regressor - 85:15 split",␣
↪size=17)
plt.show()
```



In case of Gradient Boosting Regressor Model, `t-1` variable is contributing most in the prediction of the target variable `t`.

1.7.5 Conclusion of Machine Learning Regressor Models

Using 85:15 split, below are the observations:

With baseline model, we have obtained RMSE of 4.74 on test set whereas with Decision Tree, Random Forest and Gradient Boosting models, we have got 4.80, 4.60, and 4.61, respectively.

1. Using Decision Tree Regressor, we are getting almost 100% accuracy on the training set while the test accuracy is less than 40%. In other words, our model is overfitting with decision tree regressor.
2. Using Random Forest Regressor, our results have improved a little bit. We are getting training accuracy of 95% and the test accuracy has risen to 71%. Using Feature importance, we have observed that t-1 has major role in the prediction of the target variable.
3. Using Gradient Boosting Regressor Model, we have obtained training and test accuracies of approximately 79% and 71%, respectively. Similar to Random Forest Model, `t-1` has more power in forecasting the dependent variable.

1.8 Part 5: LSTM

Read the dataset

[83]:
```
# Import the dataset
power = pd.read_excel("Solar_Power_Data_Daily.xlsx")
power.head()
```

[83]:
```
        date  Cumulative_solar_power  Daily_Solar_Power  Daily_Electricity  \
0 2011-10-26                    0.10               0.10              15.10
1 2011-10-27                   10.20              10.10               7.40
2 2011-10-28                   20.20              10.00               5.80
3 2011-10-29                   29.60               9.40               4.90
4 2011-10-30                   34.20               4.60              11.70

   Daily_Gas
0       9.00
1       9.20
2       8.00
3       6.60
4       5.30
```

[84]:
```
power['date'] = pd.to_datetime(power['date'])
power = power[(power['date'].dt.year == 2018) |(power['date'].dt.year == 2019)␣
 ↪| (power['date'].dt.year == 2020)]
power.drop(['Cumulative_solar_power', 'Daily_Electricity', 'Daily_Gas'],␣
 ↪axis=1, inplace=True)
power.reset_index(inplace=True)
```

```
power.drop('index', axis=1, inplace=True)
power.head()
```

[84]:
```
         date  Daily_Solar_Power
0 2018-01-01               1.00
1 2018-01-02               1.00
2 2018-01-03               2.00
3 2018-01-04               1.00
4 2018-01-05               0.00
```

[85]:
```
power.shape
```

[85]:
```
(1045, 2)
```

Create Array of the Data Values

[86]:
```
df = power.iloc[:,1].values
df
```

[86]:
```
array([1., 1., 2., …, 8., 5., 3.])
```

Convert Array into 1-Column Array

[87]:
```
df = df.reshape(-1,1)
df
```

[87]:
```
array([[1.],
       [1.],
       [2.],
       …,
       [8.],
       [5.],
       [3.]])
```

[88]:
```
df.dtype #Check the datatype of the array
```

[88]:
```
dtype('float64')
```

[89]:
```
# Coverting to float as Neural networks work best with floats if it is already␣
↪not there
df = df.astype('float32')
df.shape
```

[89]:
```
(1045, 1)
```

Scale the data before feeding to the algorithm

[90]:
```
# Scaling the data
scalar = MinMaxScaler()
df=scalar.fit_transform(df)
```

Split the data to predict for 30 periods

[91]:
```
# Split into train and test
train = df[:-30,:]
test = df[-30:,:]
```

[92]:
```
print(len(train), len(test))
```

```
1015 30
```

Create Data for Model Building

[93]:
```
# Building the 2D array for supervised learning
def create_data(sequence, time_stamp):
    random.seed(6)
    dataX = []
    dataY = []
    for i in range(len(sequence) - time_stamp - 1):
        a = sequence[i:(i + time_stamp), 0]
        dataX.append(a)
        dataY.append(sequence[i + time_stamp, 0])
    return np.array(dataX),  np.array(dataY)
```

Define Optimizers to use in the model compilation

[94]:
```
adam = Adam(learning_rate=0.001)
rms = RMSprop(learning_rate=0.001, momentum=0.1)
sgd = SGD(learning_rate=0.05, momentum=0.1)
```

[95]:
```
time_stamp = 1
```

Model Building (Epoch=100) and Optimizer='Adam'

[96]:
```
# Apply the 2D array function to train and test datasets
random.seed(6)
train_X, train_Y = create_data(train, time_stamp)
test_X, test_Y =create_data(test, time_stamp)
```

[97]:
```
# transform input from [samples, features] to [samples, timesteps, features]␣
↪basically from 2D to 3D
train_X = np.reshape(train_X, (train_X.shape[0],1, train_X.shape[1]))
test_X = np.reshape(test_X, (test_X.shape[0], 1, test_X.shape[1]))
```

[98]:

```
# Build the LSTM Model
random.seed(6)
model = Sequential()
# Adding the input layer and LSTM layer
model.add(LSTM(32, activation= 'relu', input_shape =(1, time_stamp)))
model.add(Dropout(0.15))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.10))
model.add(Dense(1))
```

[99]:

```
model.compile(optimizer =adam, loss='mse', metrics=['mean_absolute_error'])
model.fit(train_X, train_Y, batch_size=4, epochs = 100, verbose=2)
```

```
Epoch 1/100
254/254 - 0s - loss: 0.0649 - mean_absolute_error: 0.2013
Epoch 2/100
254/254 - 0s - loss: 0.0349 - mean_absolute_error: 0.1459
Epoch 3/100
254/254 - 0s - loss: 0.0341 - mean_absolute_error: 0.1410
Epoch 4/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1400
Epoch 5/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1385
Epoch 6/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1410
Epoch 7/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1391
Epoch 8/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1397
Epoch 9/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1388
Epoch 10/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1405
Epoch 11/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1397
Epoch 12/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1394
Epoch 13/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1394
Epoch 14/100
254/254 - 0s - loss: 0.0337 - mean_absolute_error: 0.1404
Epoch 15/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1398
Epoch 16/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1403
Epoch 17/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1388
```

```
Epoch 18/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1401
Epoch 19/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1402
Epoch 20/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1386
Epoch 21/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1391
Epoch 22/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1372
Epoch 23/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1394
Epoch 24/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1353
Epoch 25/100
254/254 - 0s - loss: 0.0322 - mean_absolute_error: 0.1379
Epoch 26/100
254/254 - 0s - loss: 0.0321 - mean_absolute_error: 0.1365
Epoch 27/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1352
Epoch 28/100
254/254 - 0s - loss: 0.0319 - mean_absolute_error: 0.1356
Epoch 29/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1379
Epoch 30/100
254/254 - 0s - loss: 0.0321 - mean_absolute_error: 0.1367
Epoch 31/100
254/254 - 0s - loss: 0.0319 - mean_absolute_error: 0.1361
Epoch 32/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1403
Epoch 33/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1391
Epoch 34/100
254/254 - 0s - loss: 0.0321 - mean_absolute_error: 0.1367
Epoch 35/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1387
Epoch 36/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1380
Epoch 37/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1402
Epoch 38/100
254/254 - 0s - loss: 0.0316 - mean_absolute_error: 0.1358
Epoch 39/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1360
Epoch 40/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1391
Epoch 41/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1408
```

```
Epoch 42/100
254/254 - 0s - loss: 0.0319 - mean_absolute_error: 0.1350
Epoch 43/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1399
Epoch 44/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1374
Epoch 45/100
254/254 - 0s - loss: 0.0316 - mean_absolute_error: 0.1353
Epoch 46/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1363
Epoch 47/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1375
Epoch 48/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1380
Epoch 49/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1376
Epoch 50/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1378
Epoch 51/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1370
Epoch 52/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1354
Epoch 53/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1383
Epoch 54/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1386
Epoch 55/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1380
Epoch 56/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1374
Epoch 57/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1383
Epoch 58/100
254/254 - 0s - loss: 0.0319 - mean_absolute_error: 0.1370
Epoch 59/100
254/254 - 0s - loss: 0.0325 - mean_absolute_error: 0.1365
Epoch 60/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1399
Epoch 61/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1360
Epoch 62/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1380
Epoch 63/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1385
Epoch 64/100
254/254 - 0s - loss: 0.0322 - mean_absolute_error: 0.1369
Epoch 65/100
254/254 - 0s - loss: 0.0321 - mean_absolute_error: 0.1368
```

```
Epoch 66/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1389
Epoch 67/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1374
Epoch 68/100
254/254 - 0s - loss: 0.0316 - mean_absolute_error: 0.1368
Epoch 69/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1373
Epoch 70/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1387
Epoch 71/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1373
Epoch 72/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1389
Epoch 73/100
254/254 - 0s - loss: 0.0316 - mean_absolute_error: 0.1362
Epoch 74/100
254/254 - 0s - loss: 0.0319 - mean_absolute_error: 0.1375
Epoch 75/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1410
Epoch 76/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1385
Epoch 77/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1384
Epoch 78/100
254/254 - 0s - loss: 0.0325 - mean_absolute_error: 0.1397
Epoch 79/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1355
Epoch 80/100
254/254 - 0s - loss: 0.0322 - mean_absolute_error: 0.1376
Epoch 81/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1380
Epoch 82/100
254/254 - 0s - loss: 0.0322 - mean_absolute_error: 0.1383
Epoch 83/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1361
Epoch 84/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1369
Epoch 85/100
254/254 - 0s - loss: 0.0321 - mean_absolute_error: 0.1377
Epoch 86/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1389
Epoch 87/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1369
Epoch 88/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1362
Epoch 89/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1375
```

```
Epoch 90/100
254/254 - 0s - loss: 0.0319 - mean_absolute_error: 0.1370
Epoch 91/100
254/254 - 0s - loss: 0.0315 - mean_absolute_error: 0.1365
Epoch 92/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1388
Epoch 93/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1395
Epoch 94/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1371
Epoch 95/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1385
Epoch 96/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1383
Epoch 97/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1364
Epoch 98/100
254/254 - 0s - loss: 0.0314 - mean_absolute_error: 0.1359
Epoch 99/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1361
Epoch 100/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1405
```

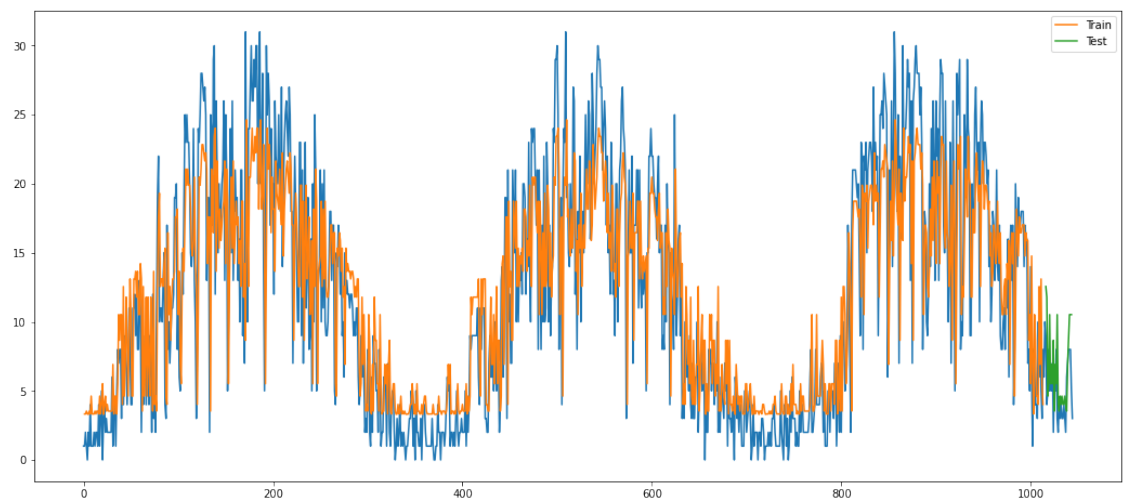
[99]:
```
<tensorflow.python.keras.callbacks.History at 0x2ed785d71f0>
```

[100]:
```
# Make predictions
train_predict = model.predict(train_X)
test_predict = model.predict(test_X)

# inverting predictions
train_predict = scalar.inverse_transform(train_predict)
train_Y = scalar.inverse_transform([train_Y])
test_predict = scalar.inverse_transform(test_predict)
test_Y = scalar.inverse_transform([test_Y])

# calculate mean absolute percentage error
#train_score = np.mean(np.divide(np.abs(train_Y[0], train_predict[:,0]),
 ↪train_Y[0], where=train_Y[0]!=0))*100
train_score = np.mean(np.abs((train_Y[0], train_predict[:,0])/(train_Y[0] +
 ↪(train_Y[0]==0))))*100
print('Train Score: %.2f MAPE' % (train_score))
#test_score = np.mean(np.divide(np.abs(test_Y[0], test_predict[:,0]),
 ↪test_Y[0], where=test_Y[0]!=0))*100
test_score = np.mean(np.abs((test_Y[0], test_predict[:,0])/(test_Y[0] +
 ↪(test_Y[0]==0))))*100
print('Test Score: %.2f MAPE' % (test_score))
```

```
# calculate root mean squared error
train_score_1 = math.sqrt(mean_squared_error(train_Y[0], train_predict[:,0]))
print('Train Score: %.3f RMSE' % (train_score_1))
test_score_1 = math.sqrt(mean_squared_error(test_Y[0], test_predict[:,0]))
print('Test Score: %.3f RMSE' % (test_score_1))
```

```
Train Score: 123.85 MAPE
Test Score: 124.86 MAPE
Train Score: 5.397 RMSE
Test Score: 3.274 RMSE
```

[101]:
```
plt.figure(figsize=(18,8))
# shifting train
train_plot = np.empty_like(df) # create an array with the same shape as provided
train_plot[:, :] = np.nan
train_plot[time_stamp:len(train_predict)+time_stamp, :] = train_predict
# shifting test predictions for plotting
test_plot = np.empty_like(df)
test_plot[:, :] = np.nan
test_plot[len(train_predict)+(time_stamp*2)+1:len(df)-1, :] = test_predict
# plot baseline and predictions
plt.plot(scalar.inverse_transform(df))
plt.plot(train_plot, label='Train')
plt.plot(test_plot, label="Test")
plt.legend()
plt.show()
```



Model Building (Epoch=100) and Optimizer='RMSprop'

[102]:
```
# Apply the 2D array function to train and test datasets
random.seed(6)
train_X, train_Y = create_data(train, time_stamp)
test_X, test_Y =create_data(test, time_stamp)
```

[103]:
```
# transform input from [samples, features] to [samples, timesteps, features]␣
↪basically from 2D to 3D
train_X = np.reshape(train_X, (train_X.shape[0],1, train_X.shape[1]))
test_X = np.reshape(test_X, (test_X.shape[0], 1, test_X.shape[1]))
```

[104]:
```
# Build the LSTM Model
random.seed(6)
model = Sequential()
# Adding the input layer and LSTM layer
model.add(LSTM(32, activation= 'relu', input_shape =(1, time_stamp)))
model.add(Dropout(0.15))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.10))
model.add(Dense(1))
```

[105]:
```
model.compile(optimizer =rms, loss='mse', metrics=['mean_absolute_error'])
model.fit(train_X, train_Y, batch_size=4, epochs = 100, verbose=2)
```

```
Epoch 1/100
254/254 - 0s - loss: 0.0515 - mean_absolute_error: 0.1854
Epoch 2/100
254/254 - 0s - loss: 0.0366 - mean_absolute_error: 0.1473
Epoch 3/100
254/254 - 0s - loss: 0.0354 - mean_absolute_error: 0.1445
Epoch 4/100
254/254 - 0s - loss: 0.0364 - mean_absolute_error: 0.1451
Epoch 5/100
254/254 - 0s - loss: 0.0357 - mean_absolute_error: 0.1464
Epoch 6/100
254/254 - 0s - loss: 0.0359 - mean_absolute_error: 0.1439
Epoch 7/100
254/254 - 0s - loss: 0.0353 - mean_absolute_error: 0.1447
Epoch 8/100
254/254 - 0s - loss: 0.0344 - mean_absolute_error: 0.1431
Epoch 9/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1415
Epoch 10/100
254/254 - 0s - loss: 0.0345 - mean_absolute_error: 0.1424
Epoch 11/100
254/254 - 0s - loss: 0.0349 - mean_absolute_error: 0.1427
Epoch 12/100
254/254 - 0s - loss: 0.0350 - mean_absolute_error: 0.1431
```

```
Epoch 13/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1399
Epoch 14/100
254/254 - 0s - loss: 0.0349 - mean_absolute_error: 0.1425
Epoch 15/100
254/254 - 0s - loss: 0.0350 - mean_absolute_error: 0.1434
Epoch 16/100
254/254 - 0s - loss: 0.0346 - mean_absolute_error: 0.1418
Epoch 17/100
254/254 - 0s - loss: 0.0357 - mean_absolute_error: 0.1462
Epoch 18/100
254/254 - 0s - loss: 0.0344 - mean_absolute_error: 0.1414
Epoch 19/100
254/254 - 0s - loss: 0.0344 - mean_absolute_error: 0.1426
Epoch 20/100
254/254 - 0s - loss: 0.0342 - mean_absolute_error: 0.1416
Epoch 21/100
254/254 - 0s - loss: 0.0342 - mean_absolute_error: 0.1419
Epoch 22/100
254/254 - 0s - loss: 0.0349 - mean_absolute_error: 0.1438
Epoch 23/100
254/254 - 0s - loss: 0.0344 - mean_absolute_error: 0.1400
Epoch 24/100
254/254 - 0s - loss: 0.0343 - mean_absolute_error: 0.1427
Epoch 25/100
254/254 - 0s - loss: 0.0342 - mean_absolute_error: 0.1424
Epoch 26/100
254/254 - 0s - loss: 0.0339 - mean_absolute_error: 0.1410
Epoch 27/100
254/254 - 0s - loss: 0.0353 - mean_absolute_error: 0.1426
Epoch 28/100
254/254 - 0s - loss: 0.0352 - mean_absolute_error: 0.1430
Epoch 29/100
254/254 - 0s - loss: 0.0347 - mean_absolute_error: 0.1422
Epoch 30/100
254/254 - 0s - loss: 0.0342 - mean_absolute_error: 0.1407
Epoch 31/100
254/254 - 0s - loss: 0.0344 - mean_absolute_error: 0.1429
Epoch 32/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1396
Epoch 33/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1397
Epoch 34/100
254/254 - 0s - loss: 0.0343 - mean_absolute_error: 0.1426
Epoch 35/100
254/254 - 0s - loss: 0.0337 - mean_absolute_error: 0.1406
Epoch 36/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1399
```

```
Epoch 37/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1386
Epoch 38/100
254/254 - 0s - loss: 0.0351 - mean_absolute_error: 0.1452
Epoch 39/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1413
Epoch 40/100
254/254 - 0s - loss: 0.0339 - mean_absolute_error: 0.1419
Epoch 41/100
254/254 - 0s - loss: 0.0352 - mean_absolute_error: 0.1431
Epoch 42/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1382
Epoch 43/100
254/254 - 0s - loss: 0.0343 - mean_absolute_error: 0.1404
Epoch 44/100
254/254 - 0s - loss: 0.0339 - mean_absolute_error: 0.1393
Epoch 45/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1402
Epoch 46/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1408
Epoch 47/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1382
Epoch 48/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1416
Epoch 49/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1408
Epoch 50/100
254/254 - 0s - loss: 0.0343 - mean_absolute_error: 0.1415
Epoch 51/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1387
Epoch 52/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1409
Epoch 53/100
254/254 - 0s - loss: 0.0343 - mean_absolute_error: 0.1410
Epoch 54/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1416
Epoch 55/100
254/254 - 0s - loss: 0.0349 - mean_absolute_error: 0.1421
Epoch 56/100
254/254 - 0s - loss: 0.0341 - mean_absolute_error: 0.1414
Epoch 57/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1422
Epoch 58/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1386
Epoch 59/100
254/254 - 0s - loss: 0.0339 - mean_absolute_error: 0.1407
Epoch 60/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1384
```

```
Epoch 61/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1393
Epoch 62/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1403
Epoch 63/100
254/254 - 0s - loss: 0.0342 - mean_absolute_error: 0.1403
Epoch 64/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1407
Epoch 65/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1370
Epoch 66/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1397
Epoch 67/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1404
Epoch 68/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1403
Epoch 69/100
254/254 - 0s - loss: 0.0344 - mean_absolute_error: 0.1420
Epoch 70/100
254/254 - 0s - loss: 0.0343 - mean_absolute_error: 0.1417
Epoch 71/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1392
Epoch 72/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1399
Epoch 73/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1371
Epoch 74/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1380
Epoch 75/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1388
Epoch 76/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1403
Epoch 77/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1392
Epoch 78/100
254/254 - 0s - loss: 0.0341 - mean_absolute_error: 0.1403
Epoch 79/100
254/254 - 0s - loss: 0.0342 - mean_absolute_error: 0.1413
Epoch 80/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1412
Epoch 81/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1395
Epoch 82/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1374
Epoch 83/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1388
Epoch 84/100
254/254 - 0s - loss: 0.0339 - mean_absolute_error: 0.1402
```

```
Epoch 85/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1410
Epoch 86/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1376
Epoch 87/100
254/254 - 0s - loss: 0.0337 - mean_absolute_error: 0.1402
Epoch 88/100
254/254 - 0s - loss: 0.0337 - mean_absolute_error: 0.1392
Epoch 89/100
254/254 - 0s - loss: 0.0339 - mean_absolute_error: 0.1401
Epoch 90/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1406
Epoch 91/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1359
Epoch 92/100
254/254 - 0s - loss: 0.0340 - mean_absolute_error: 0.1412
Epoch 93/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1401
Epoch 94/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1401
Epoch 95/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1379
Epoch 96/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1397
Epoch 97/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1364
Epoch 98/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1375
Epoch 99/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1401
Epoch 100/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1378
```

[105]:

```
<tensorflow.python.keras.callbacks.History at 0x2ed78e66ac0>
```

[106]:

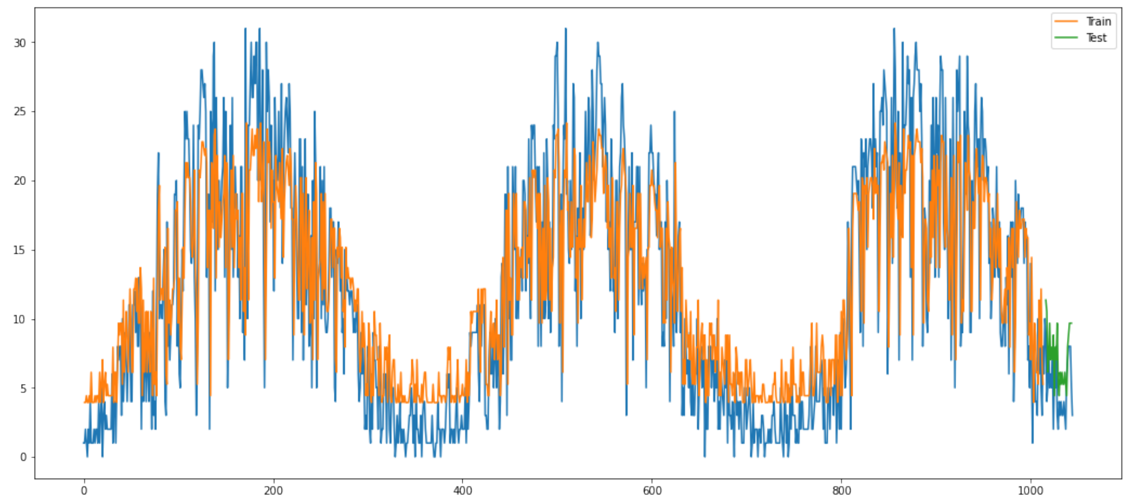
```
# Make predictions
train_predict = model.predict(train_X)
test_predict = model.predict(test_X)

# inverting predictions
train_predict = scalar.inverse_transform(train_predict)
train_Y = scalar.inverse_transform([train_Y])
test_predict = scalar.inverse_transform(test_predict)
test_Y = scalar.inverse_transform([test_Y])

# calculate mean absolute percentage error
```

```
train_score = np.mean(np.abs((train_Y[0], train_predict[:,0])/(train_Y[0] +␣
↪(train_Y[0]==0.))))*100
print('Train Score: %.2f MAPE' % (train_score))
test_score = np.mean(np.abs((test_Y[0], test_predict[:,0])/(test_Y[0] +␣
↪(test_Y[0]==0.))))*100
print('Test Score: %.2f MAPE' % (test_score))

# calculate root mean squared error
train_score_1 = math.sqrt(mean_squared_error(train_Y[0], train_predict[:,0]))
print('Train Score: %.3f RMSE' % (train_score_1))
test_score_1 = math.sqrt(mean_squared_error(test_Y[0], test_predict[:,0]))
print('Test Score: %.3f RMSE' % (test_score_1))
```

```
Train Score: 130.54 MAPE
Test Score: 133.40 MAPE
Train Score: 5.452 RMSE
Test Score: 3.133 RMSE
```

[107]:

```
plt.figure(figsize=(18,8))
# shifting train
train_plot = np.empty_like(df) # create an array with the same shape as provided
train_plot[:, :] = np.nan
train_plot[time_stamp:len(train_predict)+time_stamp, :] = train_predict
# shifting test predictions for plotting
test_plot = np.empty_like(df)
test_plot[:, :] = np.nan
test_plot[len(train_predict)+(time_stamp*2)+1:len(df)-1, :] = test_predict
# plot baseline and predictions
plt.plot(scalar.inverse_transform(df))
plt.plot(train_plot, label='Train')
plt.plot(test_plot, label='Test')
plt.legend()
plt.show()
```



Model Building (Epoch=100) and Optimizer='SGD'

[108]:
```
# Apply the 2D array function to train and test datasets
random.seed(6)
train_X, train_Y = create_data(train, time_stamp)
test_X, test_Y =create_data(test, time_stamp)
```

[109]:
```
# transform input from [samples, features] to [samples, timesteps, features]␣
↪basically from 2D to 3D
train_X = np.reshape(train_X, (train_X.shape[0],1, train_X.shape[1]))
test_X = np.reshape(test_X, (test_X.shape[0], 1, test_X.shape[1]))
```

[110]:
```
# Build the LSTM Model
random.seed(6)
model = Sequential()
# Adding the input layer and LSTM layer
model.add(LSTM(50, activation= 'relu', input_shape =(1, time_stamp)))
model.add(Dropout(0.15))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.10))
model.add(Dense(1))
```

[111]:
```
model.compile(optimizer =sgd, loss='mse', metrics=['mean_absolute_error'])
model.fit(train_X, train_Y, batch_size=4, epochs = 100, verbose=2)
```

```
Epoch 1/100
254/254 - 0s - loss: 0.0736 - mean_absolute_error: 0.2331
Epoch 2/100
254/254 - 0s - loss: 0.0614 - mean_absolute_error: 0.2149
Epoch 3/100
```

```
254/254 - 0s - loss: 0.0470 - mean_absolute_error: 0.1848
Epoch 4/100
254/254 - 0s - loss: 0.0388 - mean_absolute_error: 0.1582
Epoch 5/100
254/254 - 0s - loss: 0.0360 - mean_absolute_error: 0.1484
Epoch 6/100
254/254 - 0s - loss: 0.0374 - mean_absolute_error: 0.1518
Epoch 7/100
254/254 - 0s - loss: 0.0365 - mean_absolute_error: 0.1500
Epoch 8/100
254/254 - 0s - loss: 0.0355 - mean_absolute_error: 0.1468
Epoch 9/100
254/254 - 0s - loss: 0.0347 - mean_absolute_error: 0.1446
Epoch 10/100
254/254 - 0s - loss: 0.0356 - mean_absolute_error: 0.1458
Epoch 11/100
254/254 - 0s - loss: 0.0357 - mean_absolute_error: 0.1475
Epoch 12/100
254/254 - 0s - loss: 0.0351 - mean_absolute_error: 0.1432
Epoch 13/100
254/254 - 0s - loss: 0.0348 - mean_absolute_error: 0.1441
Epoch 14/100
254/254 - 0s - loss: 0.0359 - mean_absolute_error: 0.1471
Epoch 15/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1424
Epoch 16/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1423
Epoch 17/100
254/254 - 0s - loss: 0.0345 - mean_absolute_error: 0.1433
Epoch 18/100
254/254 - 0s - loss: 0.0361 - mean_absolute_error: 0.1461
Epoch 19/100
254/254 - 0s - loss: 0.0342 - mean_absolute_error: 0.1447
Epoch 20/100
254/254 - 0s - loss: 0.0341 - mean_absolute_error: 0.1419
Epoch 21/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1412
Epoch 22/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1411
Epoch 23/100
254/254 - 0s - loss: 0.0351 - mean_absolute_error: 0.1450
Epoch 24/100
254/254 - 0s - loss: 0.0337 - mean_absolute_error: 0.1420
Epoch 25/100
254/254 - 0s - loss: 0.0341 - mean_absolute_error: 0.1429
Epoch 26/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1426
Epoch 27/100
```

```
254/254 - 0s - loss: 0.0345 - mean_absolute_error: 0.1448
Epoch 28/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1392
Epoch 29/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1385
Epoch 30/100
254/254 - 0s - loss: 0.0341 - mean_absolute_error: 0.1411
Epoch 31/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1405
Epoch 32/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1399
Epoch 33/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1404
Epoch 34/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1396
Epoch 35/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1408
Epoch 36/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1404
Epoch 37/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1401
Epoch 38/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1413
Epoch 39/100
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1411
Epoch 40/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1404
Epoch 41/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1381
Epoch 42/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1411
Epoch 43/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1397
Epoch 44/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1404
Epoch 45/100
254/254 - 0s - loss: 0.0332 - mean_absolute_error: 0.1391
Epoch 46/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1399
Epoch 47/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1397
Epoch 48/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1401
Epoch 49/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1412
Epoch 50/100
254/254 - 0s - loss: 0.0337 - mean_absolute_error: 0.1411
Epoch 51/100
```

```
254/254 - 0s - loss: 0.0336 - mean_absolute_error: 0.1420
Epoch 52/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1386
Epoch 53/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1404
Epoch 54/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1399
Epoch 55/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1395
Epoch 56/100
254/254 - 0s - loss: 0.0325 - mean_absolute_error: 0.1386
Epoch 57/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1394
Epoch 58/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1407
Epoch 59/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1395
Epoch 60/100
254/254 - 0s - loss: 0.0337 - mean_absolute_error: 0.1422
Epoch 61/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1402
Epoch 62/100
254/254 - 0s - loss: 0.0334 - mean_absolute_error: 0.1407
Epoch 63/100
254/254 - 0s - loss: 0.0325 - mean_absolute_error: 0.1382
Epoch 64/100
254/254 - 0s - loss: 0.0338 - mean_absolute_error: 0.1409
Epoch 65/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1395
Epoch 66/100
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1408
Epoch 67/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1391
Epoch 68/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1392
Epoch 69/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1407
Epoch 70/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1387
Epoch 71/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1404
Epoch 72/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1383
Epoch 73/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1389
Epoch 74/100
254/254 - 0s - loss: 0.0320 - mean_absolute_error: 0.1377
Epoch 75/100
```

```
254/254 - 0s - loss: 0.0333 - mean_absolute_error: 0.1404
Epoch 76/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1394
Epoch 77/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1407
Epoch 78/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1414
Epoch 79/100
254/254 - 0s - loss: 0.0318 - mean_absolute_error: 0.1377
Epoch 80/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1399
Epoch 81/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1410
Epoch 82/100
254/254 - 0s - loss: 0.0330 - mean_absolute_error: 0.1393
Epoch 83/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1383
Epoch 84/100
254/254 - 0s - loss: 0.0331 - mean_absolute_error: 0.1402
Epoch 85/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1390
Epoch 86/100
254/254 - 0s - loss: 0.0317 - mean_absolute_error: 0.1370
Epoch 87/100
254/254 - 0s - loss: 0.0321 - mean_absolute_error: 0.1374
Epoch 88/100
254/254 - 0s - loss: 0.0319 - mean_absolute_error: 0.1377
Epoch 89/100
254/254 - 0s - loss: 0.0314 - mean_absolute_error: 0.1371
Epoch 90/100
254/254 - 0s - loss: 0.0335 - mean_absolute_error: 0.1413
Epoch 91/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1398
Epoch 92/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1377
Epoch 93/100
254/254 - 0s - loss: 0.0329 - mean_absolute_error: 0.1400
Epoch 94/100
254/254 - 0s - loss: 0.0323 - mean_absolute_error: 0.1389
Epoch 95/100
254/254 - 0s - loss: 0.0325 - mean_absolute_error: 0.1377
Epoch 96/100
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1398
Epoch 97/100
254/254 - 0s - loss: 0.0328 - mean_absolute_error: 0.1398
Epoch 98/100
254/254 - 0s - loss: 0.0324 - mean_absolute_error: 0.1377
Epoch 99/100
```

```
254/254 - 0s - loss: 0.0326 - mean_absolute_error: 0.1379
Epoch 100/100
254/254 - 0s - loss: 0.0327 - mean_absolute_error: 0.1383
```

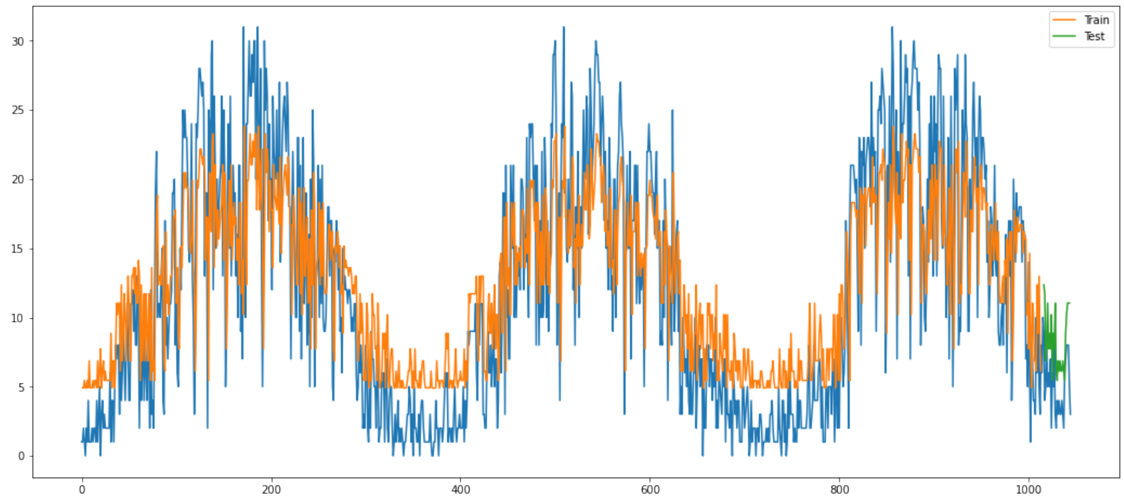
[111]: <tensorflow.python.keras.callbacks.History at 0x2ed7b8f2ee0>

[112]:
```python
# Make predictions
train_predict = model.predict(train_X)
test_predict = model.predict(test_X)

# inverting predictions
train_predict = scalar.inverse_transform(train_predict)
train_Y = scalar.inverse_transform([train_Y])
test_predict = scalar.inverse_transform(test_predict)
test_Y = scalar.inverse_transform([test_Y])

# calculate mean absolute percentage error
train_score = np.mean(np.abs((train_Y[0], train_predict[:,0])/(train_Y[0] +␣
↪(train_Y[0]==0.))))*100
print('Train Score: %.2f MAPE' % (train_score))
test_score = np.mean(np.abs((test_Y[0], test_predict[:,0])/(test_Y[0] +␣
↪(test_Y[0]==0.))))*100
print('Test Score: %.2f MAPE' % (test_score))

# calculate root mean squared error
train_score_1 = math.sqrt(mean_squared_error(train_Y[0], train_predict[:,0]))
print('Train Score: %.3f RMSE' % (train_score_1))
test_score_1 = math.sqrt(mean_squared_error(test_Y[0], test_predict[:,0]))
print('Test Score: %.3f RMSE' % (test_score_1))
```

```
Train Score: 138.78 MAPE
Test Score: 145.19 MAPE
Train Score: 5.542 RMSE
Test Score: 3.962 RMSE
```

[113]:
```python
plt.figure(figsize=(18,8))

# shifting train
train_plot = np.empty_like(df) # create an array with the same shape as provided
train_plot[:, :] = np.nan
train_plot[time_stamp:len(train_predict)+time_stamp, :] = train_predict
# shifting test predictions for plotting
test_plot = np.empty_like(df)
test_plot[:, :] = np.nan
test_plot[len(train_predict)+(time_stamp*2)+1:len(df)-1, :] = test_predict
# plot baseline and predictions
plt.plot(scalar.inverse_transform(df))
```

```
plt.plot(train_plot, label='Train')
plt.plot(test_plot, label='Test')
plt.legend()
plt.show()
```



1.8.1 Conclusion for LSTM

Using LSTM Deep Learning Model, we can observe that we are getting optimum results when we used different optimizers. As illustrated in the plots, we have minimum deviation of the predicted values from the actual values using LSTM Model.

Using 100 epochs for LSTM model, we have observed the following results:
1. Using SGD and Adam optimizers for compilation, we have got 3.962 and 3.274, respectively of RMSE on Test Set, which are bit on the higher side.
2. Using RMSprop optimizer for compilation, we have got 3.133 of root mean squared error (RMSE) on Test Set.

To sum up, we have minimum error using LSTM model.

1.9 Conclusion

To conclude, we are getting better results in those cases where we have minimum deviation of the forecasted values from the actual values. We are measuring this deviation in the form of root mean squared error (RMSE) which is defined by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2)}{N}}$$

Evaluation of the forecasting technique is done with the criteria that minimum the deviation or error value, the most likely the technique will predict better. Keeping this in mind, we have minimum value of RMSE is in case of Exponential Smoothing and LSTM Model.