INTRODUCTION

Traditional power plants can control how much power they produce which allows for power grid operators to easily manage supply and demand. However, most of these traditioanl power plants are coal powered, which are a massive source of air pollution. Integrating renewable energy power plants into the grid would greatly help reduce pollution, however renewable energy sources like solar and wind have variable output since they depend on other factors, primarily the weather. For example, a solar farm will produce more electricity on sunny days than on cloudy days, and this makes it difficult for grid operators to manage supply and demand. Forecasting power output for variable renewable energy sources can help here in that the operators can then know how much power to expect in the future, and if it isn't enough to meet the demand, they can have a traditional power plant on standby, and power it up when the the supply dips below what is needed. The idea here is that by forecasting power output of a solar plant, we can balance it with other sources of power generation.

My goal in this project is to accomplish this by using machine learning algorithms for time series forecasting. I'm going to use 3 different alogorithms: SARIMA, Facebook PROPHET, and SARIMAX. And then compare them to see which performs the best.

let's start by importing the necessary libraries.

Importing Libraries

In [308]:

```python
import pandas as pd
from pandas.tseries.offsets import DateOffset
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('darkgrid')
import numpy as np

# metrics
from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose

# models
from pmdarima.arima import auto_arima
from statsmodels.tsa.statespace.sarimax import SARIMAX
from fbprophet import Prophet

# api
import json
import requests
```

Importing Data & Data Understanding

POWER OUTPUT DATA:

In [33]:

```python
# power output data for plant 1
p1_gen = pd.read_csv('../../data/Plant_1_Generation_Data.csv')
```

In [34]:

```
# looking at the first 5 records:

p1_gen.head()
```

Out[34]:

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_
0	15-05-2020 00:00	4135001	1BY6WEcLGh8j5v7	0.0	0.0	0.0	625
1	15-05-2020 00:00	4135001	1IF53ai7Xc0U56Y	0.0	0.0	0.0	618
2	15-05-2020 00:00	4135001	3PZuoBAID5Wc2HD	0.0	0.0	0.0	698
3	15-05-2020 00:00	4135001	7JYdWkrLSPkdwr4	0.0	0.0	0.0	760
4	15-05-2020 00:00	4135001	McdE0feGgRqW7Ca	0.0	0.0	0.0	715

Columns:

DATE_TIME: Date and timestamp of datapoint- taken every 15 minute

PLANT_ID: ID of Plant 1

SOURCE_KEY: Inverter ID

DC_POWER: DC power produced by inverter in that 15 minute interval (in kW)

AC_POWER: AC power produced by inverter in that 15 minute interval (in kW)

DAILY_YIELD: Total power produced till that point in time

TOTAL_YIELD: Total yield for the inverter till that point in time

Looking at the info below, we can see there are no missing nor duplicated values.

In [35]:

```
p1_gen.info()
print('\n')
print ("Number of duplicate values: ", p1_gen.duplicated().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68778 entries, 0 to 68777
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   DATE_TIME    68778 non-null  object 
 1   PLANT_ID     68778 non-null  int64  
 2   SOURCE_KEY   68778 non-null  object 
 3   DC_POWER     68778 non-null  float64
 4   AC_POWER     68778 non-null  float64
 5   DAILY_YIELD  68778 non-null  float64
 6   TOTAL_YIELD  68778 non-null  float64
dtypes: float64(4), int64(1), object(2)
memory usage: 3.7+ MB


Number of duplicate values:  0
```

INVERTERS:

There are 22 inverters, each with a unique ID. So each specific timestamp has 22 records for each inverter.

In [36]:

```
print("Number of unique Inverter IDs: ", len(p1_gen.SOURCE_KEY.unique()))
p1_gen.SOURCE_KEY.unique()
```

```
Number of unique Inverter IDs:  22
```

Out[36]:

```
array(['1BY6WEcLGh8j5v7', '1IF53ai7Xc0U56Y', '3PZuoBAID5Wc2HD',
       '7JYdWkrLSPkdwr4', 'McdE0feGgRqW7Ca', 'VHMLBKoKgIrUVDU',
       'WRmjgnKYAwPKWDb', 'ZnxXDlPa8U1GXgE', 'ZoEaEvLYb1n2sOq',
       'adLQvlD726eNBSB', 'bvBOhCH3iADSZry', 'iCRJl6heRkivqQ3',
       'ih0vzX44oOqAx2f', 'pkci93gMrogZuBj', 'rGa61gmuvPhdLxV',
       'sjndEbLyjtCKgGv', 'uHbuxQJl8lW7ozc', 'wCURE6d3bPkepu2',
       'z9Y9gH1T5YWrNuG', 'zBIq5rxdHJRwDNY', 'zVJPv84UY57bAof',
       'YxYtjZvoooNbGkE'], dtype=object)
```

WEATHER DATA:

In [37]:

```
# weather data for plant 1
p1_wthr = pd.read_csv('../../data/Plant_1_Weather_Sensor_Data.csv')
```

In [38]:

```
# looking at the first 5 records:

p1_wthr.head()
```

Out[38]:

	DATE_TIME	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATU
0	2020-05-15 00:00:00	4135001	HmiyD2TTLFNqkNe	25.184316	22.857
1	2020-05-15 00:15:00	4135001	HmiyD2TTLFNqkNe	25.084589	22.761
2	2020-05-15 00:30:00	4135001	HmiyD2TTLFNqkNe	24.935753	22.592
3	2020-05-15 00:45:00	4135001	HmiyD2TTLFNqkNe	24.846130	22.360
4	2020-05-15 01:00:00	4135001	HmiyD2TTLFNqkNe	24.621525	22.165

Columns:

DATE_TIME: Date and timestamp of the datapoint- taken every 15 minutes. Same as above

SOURCE_KEY: Module ID of the weather sensor

AMBIENT_TEMPERATURE: Weather temperature

MODULE_TEMPERATURE: Solar panel temperature

IRRADIATION: Amount of irradiation for the 15 minute interval.

Confirming the SOURCE_KEY here is different from the inverter IDs above:

In [39]:

```
# confiming weather sensor SOURCE_KEY is different from the ones in the gen df

p1_wthr.SOURCE_KEY.unique() in p1_gen.SOURCE_KEY.unique()
```

Out[39]:

```
False
```

Looking at the info below, we can see there are no missing nor duplicated values.

In [40]:

```
p1_wthr.info()
print ("Number of duplicate values: ", p1_wthr.duplicated().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3182 entries, 0 to 3181
Data columns (total 6 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   DATE_TIME            3182 non-null   object 
 1   PLANT_ID             3182 non-null   int64  
 2   SOURCE_KEY           3182 non-null   object 
 3   AMBIENT_TEMPERATURE  3182 non-null   float64
 4   MODULE_TEMPERATURE   3182 non-null   float64
 5   IRRADIATION          3182 non-null   float64
dtypes: float64(3), int64(1), object(2)
memory usage: 149.3+ KB
Number of duplicate values:  0
```

CHECKING FOR STATIONARITY

A time series data is said to be stationary if its statistical properties, such as mean, variance, etc, remain constant over time. When doing time series modeling, it is important that our data is stationary. This is because if our dataset shows a particular behavior over time, there is a very high probability that it will follow a similar behavior in the future.

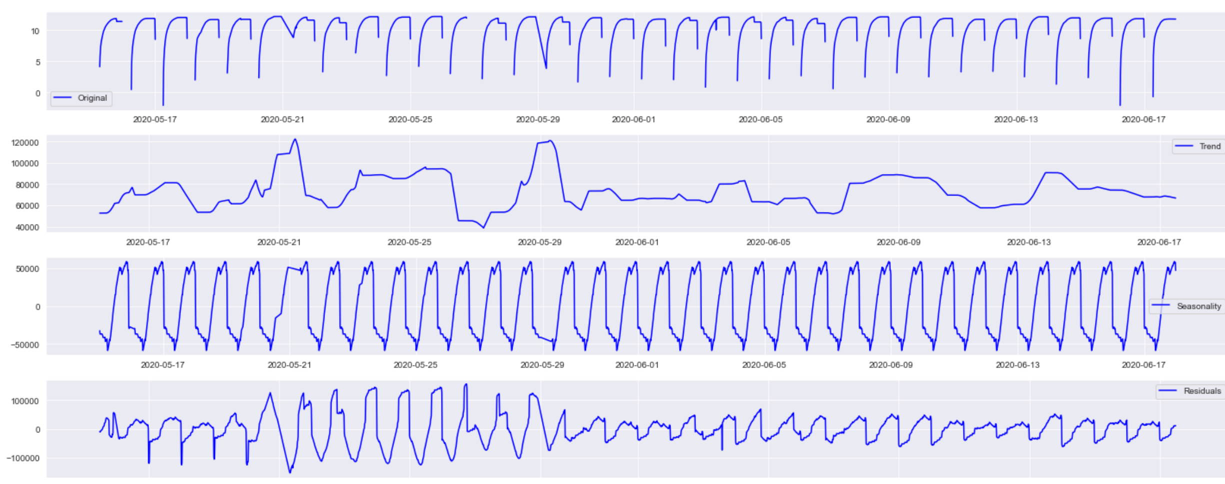
The plot below shows that our power output dataset has daily seasonality, therefore it is NOT stationary. Which makes sense since the power output peaks during the day when the sun is out, and drops during the night.

I'm going to take care of this by tuning the respective model parameters in the modeling section.

In [328]:

```
# Below I'm going to group all the inverters together by date_time, and sum the daily_yield
df = p1_gen.groupby(p1_gen.index).sum()[['DAILY_YIELD']]

# period equals 96 because that is the number of 15 minute periods we have in a day.
decomposition = seasonal_decompose(df, period=96)
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

plt.figure(figsize=(20,8))
plt.title('Seasonal Decomposition \n Plant 1 Daily Yield', size=19)
plt.subplot(411)
plt.plot(np.log(df), label='Original', color='blue')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend, label='Trend', color='blue')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonality', color='blue')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual, label='Residuals', color='blue')
plt.legend(loc='best')
plt.tight_layout()
plt.savefig('seasonal_decomp.png');
```

```
<ipython-input-328-9d06fbaab3d8>:13: RuntimeWarning: divide by zero encountered in log
  plt.plot(np.log(df), label='Original', color='blue')
```



Data Preparation For Modeling

We need to first set the date_time column as the index for both dataframes:

In [41]:

```
# power output data for plant 1:

# converting date_time column to date_time object
p1_gen.DATE_TIME = pd.to_datetime(p1_gen.DATE_TIME, infer_datetime_format=True)
p1_wthr.DATE_TIME = pd.to_datetime(p1_wthr.DATE_TIME, infer_datetime_format=True
)

# setting the date_time column as the index
p1_gen.set_index('DATE_TIME', inplace=True)
p1_wthr.set_index('DATE_TIME', inplace=True)
```

In [42]:

```
p1_gen.head()
```

Out[42]:

	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YI
DATE_TIME						
2020-05-15	4135001	1BY6WEcLGh8j5v7	0.0	0.0	0.0	62595
2020-05-15	4135001	1IF53ai7Xc0U56Y	0.0	0.0	0.0	61836
2020-05-15	4135001	3PZuoBAID5Wc2HD	0.0	0.0	0.0	69877
2020-05-15	4135001	7JYdWkrLSPkdwr4	0.0	0.0	0.0	76029
2020-05-15	4135001	McdE0feGgRqW7Ca	0.0	0.0	0.0	71589

In [43]:

```
p1_wthr.head()
```

Out[43]:

	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE
DATE_TIME				
2020-05-15 00:00:00	4135001	HmiyD2TTLFNqkNe	25.184316	22.857507
2020-05-15 00:15:00	4135001	HmiyD2TTLFNqkNe	25.084589	22.761668
2020-05-15 00:30:00	4135001	HmiyD2TTLFNqkNe	24.935753	22.592306
2020-05-15 00:45:00	4135001	HmiyD2TTLFNqkNe	24.846130	22.360852
2020-05-15 01:00:00	4135001	HmiyD2TTLFNqkNe	24.621525	22.165423

Isolating the last 5 days of power output data (6/13 to 6/17), and grouping daily_yield by date_time:

In [46]:

```
pred_gen = p1_gen[(p1_gen.index.month == 6) &
                  (p1_gen.index.day >= 13) &
                  (p1_gen.index.day <= 17)].groupby('DATE_TIME').sum()[['DAILY_YI
ELD']]
pred_gen
```

Out[46]:

	DAILY_YIELD
DATE_TIME	
2020-06-13 00:00:00	5683.214286
2020-06-13 00:15:00	0.000000
2020-06-13 00:30:00	0.000000
2020-06-13 00:45:00	0.000000
2020-06-13 01:00:00	0.000000
...	...
2020-06-17 22:45:00	129571.000000
2020-06-17 23:00:00	129571.000000
2020-06-17 23:15:00	129571.000000
2020-06-17 23:30:00	129571.000000
2020-06-17 23:45:00	127962.767857

478 rows × 1 columns

Isolating the last 5 days of weather sensor data:

In [48]:

```
pred_wthr = p1_wthr[(p1_wthr.index.month == 6) &
                    (p1_wthr.index.day >= 13) &
                    (p1_wthr.index.day <= 17)]
pred_wthr
```

Out[48]:

	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE
DATE_TIME				
2020-06-13 00:00:00	4135001	HmiyD2TTLFNqkNe	21.771613	19.357530
2020-06-13 00:15:00	4135001	HmiyD2TTLFNqkNe	21.730046	19.504081
2020-06-13 00:30:00	4135001	HmiyD2TTLFNqkNe	21.687068	19.562803
2020-06-13 00:45:00	4135001	HmiyD2TTLFNqkNe	21.619232	19.559182
2020-06-13 01:00:00	4135001	HmiyD2TTLFNqkNe	21.625968	19.787058
...	...	...	...	...
2020-06-17 22:45:00	4135001	HmiyD2TTLFNqkNe	22.150570	21.480377
2020-06-17 23:00:00	4135001	HmiyD2TTLFNqkNe	22.129816	21.389024
2020-06-17 23:15:00	4135001	HmiyD2TTLFNqkNe	22.008275	20.709211
2020-06-17 23:30:00	4135001	HmiyD2TTLFNqkNe	21.969495	20.734963
2020-06-17 23:45:00	4135001	HmiyD2TTLFNqkNe	21.909288	20.427972

480 rows × 5 columns

Here we can see that our weather sensor data has 2 extra rows (480 vs 478), meaning our power output data is missing those 2 rows.

FILLING IN MISSING ROWS

Creating a merged df with an indicator column (_merge) letting us know which df the row came from:

In [50]:

```
df_with_indicator = pd.merge(pred_wthr, pred_gen,
                              left_index=True, right_index=True,
                              how='outer', suffixes=('','_y'), indicator=True)
df_with_indicator
```

Out[50]:

	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE
DATE_TIME				
2020-06-13 00:00:00	4135001	HmiyD2TTLFNqkNe	21.771613	19.357530
2020-06-13 00:15:00	4135001	HmiyD2TTLFNqkNe	21.730046	19.504081
2020-06-13 00:30:00	4135001	HmiyD2TTLFNqkNe	21.687068	19.562803
2020-06-13 00:45:00	4135001	HmiyD2TTLFNqkNe	21.619232	19.559182
2020-06-13 01:00:00	4135001	HmiyD2TTLFNqkNe	21.625968	19.787058
...	...	...	...	...
2020-06-17 22:45:00	4135001	HmiyD2TTLFNqkNe	22.150570	21.480377
2020-06-17 23:00:00	4135001	HmiyD2TTLFNqkNe	22.129816	21.389024
2020-06-17 23:15:00	4135001	HmiyD2TTLFNqkNe	22.008275	20.709211
2020-06-17 23:30:00	4135001	HmiyD2TTLFNqkNe	21.969495	20.734963
2020-06-17 23:45:00	4135001	HmiyD2TTLFNqkNe	21.909288	20.427972

480 rows × 7 columns

Isolating rows where the merge column = 'left only', indicating it came from p1_wthr:

In [53]:

```
rows_in_df1_not_in_df2 = df_with_indicator[df_with_indicator['_merge']=='left_only'][pred_wthr.columns]

rows_in_df1_not_in_df2
```

Out[53]:

	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE
DATE_TIME				
2020-06-17 06:15:00	4135001	HmiyD2TTLFNqkNe	22.093398	20.822978
2020-06-17 06:30:00	4135001	HmiyD2TTLFNqkNe	22.275627	21.973568

Below we see that that we're missing records for 6:15am & 6:30am on 6/17/2020.

It also looks like, due to the time of day, no power was generated.

So we're going to add these date_time records with a daily yield of 0 to the power output data.

In [28]:

```
# Confirming the above data is missing from power output data:

pred_6_13[(pred_6_13.index >= '2020-06-17 06:00:00') & (pred_6_13.index <= '2020-06-17 07:00:00')]

# looks like it's just missing. the daily yield here was most likely 0 for both time stamps
```

Out[28]:

	DAILY_YIELD
DATE_TIME	
2020-06-17 06:00:00	0.000000
2020-06-17 06:45:00	0.500000
2020-06-17 07:00:00	362.660714

In [56]:

```
# adding rows with index '2020-06-17 06:15:00' & '2020-06-17 06:30:00', with col
val of 0, to end of df
pred_gen.loc[pd.to_datetime('2020-06-17 06:15:00')] = 0
pred_gen.loc[pd.to_datetime('2020-06-17 06:30:00')] = 0

# sorting df by index and setting in place
pred_gen.sort_index(inplace=True)

# confirming row was inserted correctly
pred_gen[(pred_gen.index >= '2020-06-17 06:00:00') & (pred_gen.index <= '2020-06
-17 07:00:00')]
```

Out[56]:

	DAILY_YIELD
DATE_TIME	
2020-06-17 06:00:00	0.000000
2020-06-17 06:15:00	0.000000
2020-06-17 06:30:00	0.000000
2020-06-17 06:45:00	0.500000
2020-06-17 07:00:00	362.660714

In [57]:

```
print('pred_gen records: ', len(pred_gen))
print('pred_wthr records: ', len(pred_wthr))
```

```
pred_gen records:  480
pred_wthr records:  480
```

FINAL COMBINED DATAFRAME FOR OUR MODEL

We're only going to use ambient temperature from our weather sensor data in this project, so that is the only column we're going to add to our final dataframe here.

In [60]:

```python
pred_final = pred_gen.merge(pred_wthr[['AMBIENT_TEMPERATURE']],
                left_index=True, right_index=True)
pred_final
```

Out[60]:

	DAILY_YIELD	AMBIENT_TEMPERATURE
DATE_TIME		
2020-06-13 00:00:00	5683.214286	21.771613
2020-06-13 00:15:00	0.000000	21.730046
2020-06-13 00:30:00	0.000000	21.687068
2020-06-13 00:45:00	0.000000	21.619232
2020-06-13 01:00:00	0.000000	21.625968
...	...	...
2020-06-17 22:45:00	129571.000000	22.150570
2020-06-17 23:00:00	129571.000000	22.129816
2020-06-17 23:15:00	129571.000000	22.008275
2020-06-17 23:30:00	129571.000000	21.969495
2020-06-17 23:45:00	127962.767857	21.909288

480 rows × 2 columns

TRAIN/TEST SPLIT

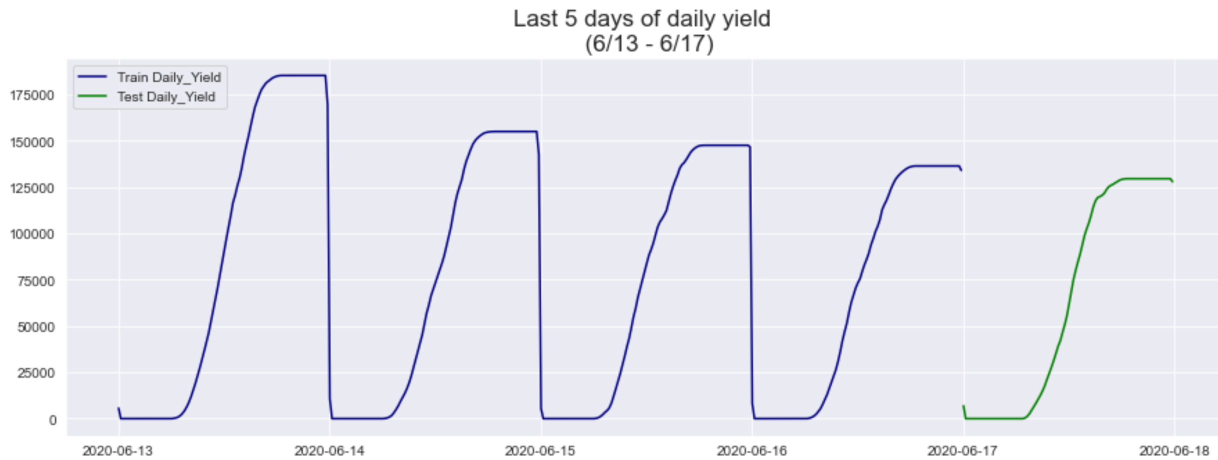
In [61]:

```python
eotri = round(pred_final.shape[0] * .8)

train_pred_fin = pred_final[:eotri]

test_pred_fin = pred_final[eotri:]

print(train_pred_fin.shape, test_pred_fin.shape)
```

```
(384, 2) (96, 2)
```

In [331]:

```
fig,ax = plt.subplots(figsize=(15,5))
ax.plot(train_pred_fin.DAILY_YIELD, label='Train Daily_Yield', color='navy')
ax.plot(test_pred_fin.DAILY_YIELD, label='Test Daily_Yield', color='green')
ax.set_title('Last 5 days of daily yield \n (6/13 - 6/17)', fontsize=17)
ax.legend(loc='upper left');
plt.savefig('train_test_data.png')
```



Modeling 1: SARIMA

SARIMA stands for Seasonal AutoRegressive Integrated Moving Average, and is a very popular time series forecasting model.

For our first model, we're only going to use the DAILY_YIELD to forecast forward, let's go ahead and isolate that feature:

In [62]:

```
train_sarima = train_pred_fin[['DAILY_YIELD']]
test_sarima = test_pred_fin[['DAILY_YIELD']]
```

In [65]:

```
train_sarima.head()
```

Out[65]:

	DAILY_YIELD
DATE_TIME	
2020-06-13 00:00:00	5683.214286
2020-06-13 00:15:00	0.000000
2020-06-13 00:30:00	0.000000
2020-06-13 00:45:00	0.000000
2020-06-13 01:00:00	0.000000

In [66]:

```
test_sarima.head()
```

Out[66]:

	DAILY_YIELD
DATE_TIME	
2020-06-17 00:00:00	6955.232143
2020-06-17 00:15:00	0.000000
2020-06-17 00:30:00	0.000000
2020-06-17 00:45:00	0.000000
2020-06-17 01:00:00	0.000000

STATIONARITY

As mentioned in the data understanding section above, the power output dataset exhibits daily seasonality, meaning that the dataset is NOT stationary. We can further confirm this by doing a **Dicky-Fuller Test**, which is a statistical test for checking stationarity.

The test assumes a null-hypothesis that the time series is not stationary. So if the test statistics is less than the critical value, we then reject that null hypothesis and say that the series is stationary.

This is not the case with our dataset, as we can see below. The test statistic is greater than the critical value at 5%, confirming that our dataset is not stationary.

I'm going take care of this by tuning parameters within each of the models.

In [316]:

```
dftest = adfuller(pred_final['DAILY_YIELD'])

# Extract and display test results in a user friendly manner
dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', '#Lags Use
d', 'Number of Observations Used'])
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value

print ('Results of Dickey-Fuller test: \n')

print(dfoutput)

print('-'*15)

if dftest[0] <= dftest[4]['5%']:
    print("strong evidence against the null hypothesis, reject the null hypothes
is. Data is stationary")
else:
    print("weak evidence against null hypothesis, indicating the data is NON-sta
tionary ")
```

```
Results of Dickey-Fuller test: 

Test Statistic                  -2.600505
p-value                          0.092893
#Lags Used                       1.000000
Number of Observations Used    478.000000
Critical Value (1%)             -3.444105
Critical Value (5%)             -2.867606
Critical Value (10%)            -2.570001
dtype: float64
---------------
weak evidence against null hypothesis, indicating the data is NON-st
ationary
```

AUTO-ARIMA

--> **ENTER EXPLANATION AIC (since that is what we're minimizing here)** <--

In [94]:

```
auto_arima(train_sarima,
           start_p=0,d=1,start_q=0,
           max_p=4,max_d=4,max_q=4,
           start_P=0,D=1,start_Q=0,
           max_P=1,max_D=1,max_Q=1,m=96,
           seasonal=True,
           error_action='warn',trace=True,
           supress_warning=True,stepwise=True,
           random_state=20,n_fits=1)
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,1,0)[96]             : AIC=5102.205, Time=2.27 sec
 ARIMA(1,1,0)(1,1,0)[96]             : AIC=4821.779, Time=36.44 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(0,1,1)(0,1,1)[96]             : AIC=4895.577, Time=10.77 sec
 ARIMA(1,1,0)(0,1,0)[96]             : AIC=5088.074, Time=2.05 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(1,1,0)(1,1,1)[96]             : AIC=4811.024, Time=76.08 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(1,1,0)(0,1,1)[96]             : AIC=4894.495, Time=14.32 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(0,1,0)(1,1,1)[96]             : AIC=4934.987, Time=25.79 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
```

```
 ARIMA(2,1,0)(1,1,1)[96]             : AIC=4897.523, Time=34.52 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(1,1,1)(1,1,1)[96]             : AIC=4898.438, Time=34.51 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(0,1,1)(1,1,1)[96]             : AIC=4897.373, Time=27.78 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:963: UserWarning: Non-stationary starting auto
regressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:975: UserWarning: Non-invertible starting MA p
arameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(2,1,1)(1,1,1)[96]             : AIC=4899.901, Time=45.03 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(1,1,0)(1,1,1)[96] intercept   : AIC=4812.288, Time=67.98 sec

Best model:  ARIMA(1,1,0)(1,1,1)[96]
Total fit time: 377.823 seconds
```

Out[94]:

```
ARIMA(order=(1, 1, 0), scoring_args={}, seasonal_order=(1, 1, 1, 96)
,
      with_intercept=False)
```

TRAIN/TEST MODEL, AND IN-SAMPLE PREDICTION

FITTING MODEL TO TRAIN DATA

In [212]:

```
p,d,q = [1,1,0]
P,D,Q,s = [1,1,1,96]

sarima_model = SARIMAX(endog=train_sarima,
                       order=(p,d,q),
                       seasonal_order=(P,D,Q,s),
                       freq='15T').fit()
```

```
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
```

MAKING PREDICTIONS AGAINST TRAIN AND TEST DATA (y_hats)

In [213]:

```
train_sarima_y_hat = pd.DataFrame(sarima_model.predict(typ='levels'), columns=['
pred_daily_yld'])

test_sarima_y_hat = pd.DataFrame(sarima_model.predict(start=test_sarima.index[0]
,
                                                     end=test_sarima.index[-1],
                                                     typ='levels'), columns=['p
red_daily_yld'])

# zero out negative predictions:
train_sarima_y_hat[train_sarima_y_hat < 0] = 0

test_sarima_y_hat[test_sarima_y_hat < 0] = 0
```

In [214]:

```
train_sarima_y_hat.head()
```

Out[214]:

	pred_daily_yld
2020-06-13 00:00:00	0.000000
2020-06-13 00:15:00	5811.320199
2020-06-13 00:30:00	0.000000
2020-06-13 00:45:00	0.000000
2020-06-13 01:00:00	0.000000

In [215]:

```
test_sarima_y_hat.head()
```

Out[215]:

	pred_daily_yld
2020-06-17 00:00:00	0.0
2020-06-17 00:15:00	0.0
2020-06-17 00:30:00	0.0
2020-06-17 00:45:00	0.0
2020-06-17 01:00:00	0.0

PERFORMANCE METRICS; PLOTTING

In [329]:

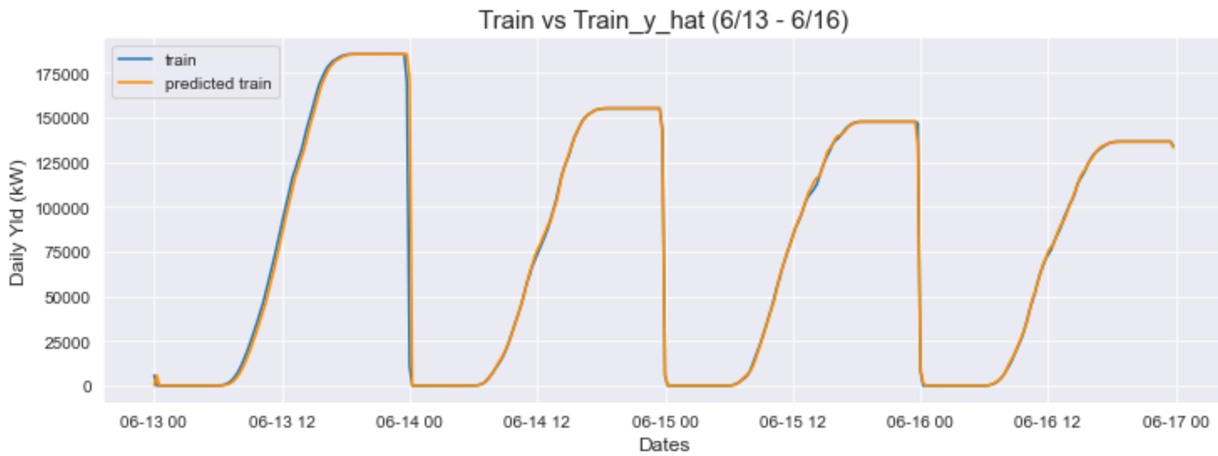
```
print('SARIMA train R2 Score: %f' % (r2_score(train_sarima.DAILY_YIELD,
                                              train_sarima_y_hat.pred_daily_yld)
))
print('SARIMA test R2 Score: %f' % (r2_score(test_sarima.DAILY_YIELD,
                                              test_sarima_y_hat.pred_daily_yld))
)

print('-'*15)


print('SARIMA train MAE Score: %f' % (mean_absolute_error(train_sarima.DAILY_YIE
LD,
                                                          train_sarima_y_hat.pre
d_daily_yld)))
print('SARIMA test MAE Score: %f' % (mean_absolute_error(test_sarima.DAILY_YIELD
```

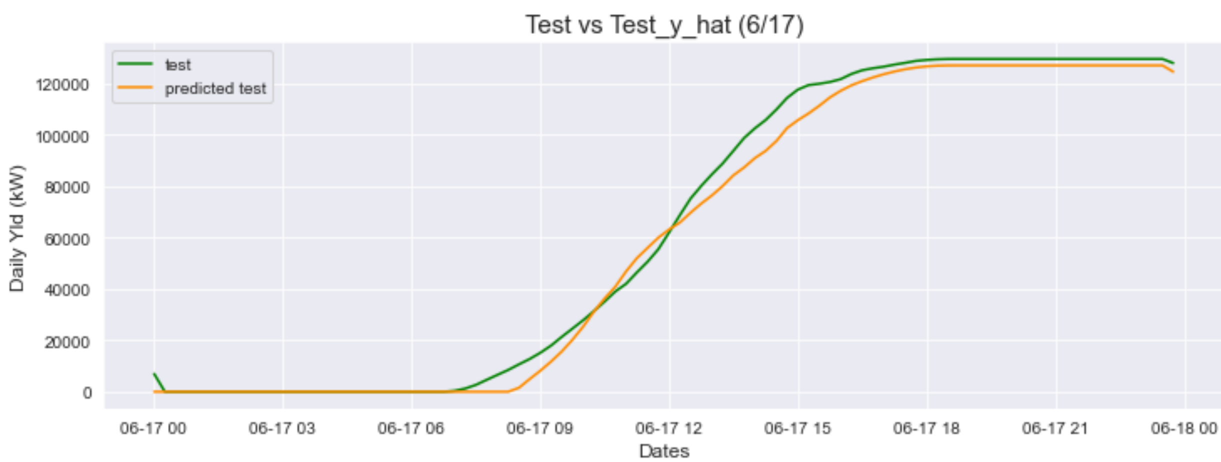
```
,
                                                           test_sarima_y_hat.pred
_daily_yld)))

print('-'*15)


print('SARIMA train RMSE Score: %f' % (mean_squared_error(train_sarima.DAILY_YIE
LD,
                                                           train_sarima_y_hat.pre
d_daily_yld,
                                                           squared=False)))
print('SARIMA test RMSE Score: %f' % (mean_squared_error(test_sarima.DAILY_YIELD
,
                                                           test_sarima_y_hat.pred
_daily_yld,
                                                           squared=False)))

print('-'*15, '\n')


print(sarima_model.summary())


print('-'*15)


fig, ax1 = plt.subplots(figsize=(12,4))
ax1.plot(train_sarima, label='train')
ax1.plot(train_sarima_y_hat, label='predicted train', c='darkorange')
ax1.legend(loc='upper left')
ax1.set_title('Train vs Train_y_hat (6/13 - 6/16)', size=15)
ax1.set_ylabel('Daily Yld (kW)', size=12)
ax1.set_xlabel('Dates', size=12)

fig, ax2 = plt.subplots(figsize=(12,4))
ax2.plot(test_sarima, label='test', c='g')
ax2.plot(test_sarima_y_hat, label='predicted test', c='darkorange')
ax2.legend(loc='upper left')
ax2.set_title('Test vs Test_y_hat (6/17)', size=15)
ax2.set_ylabel('Daily Yld (kW)', size=12)
ax2.set_xlabel('Dates', size=12)

fig, ax3 = plt.subplots(figsize=(12,4))
ax3.plot(train_sarima, label='train')
ax3.plot(test_sarima, label='test', c='g')
ax3.plot(test_sarima_y_hat, label='predicted test', c='darkorange')
ax3.legend(loc='upper left')
ax3.set_title('Train, Test, & Prediction \n 6/13 - 6/17', size=15)
ax3.set_ylabel('Daily Yld (kW)', size=12)
ax3.set_xlabel('Dates', size=12);
# plt.savefig('sarime_pred.png')
```

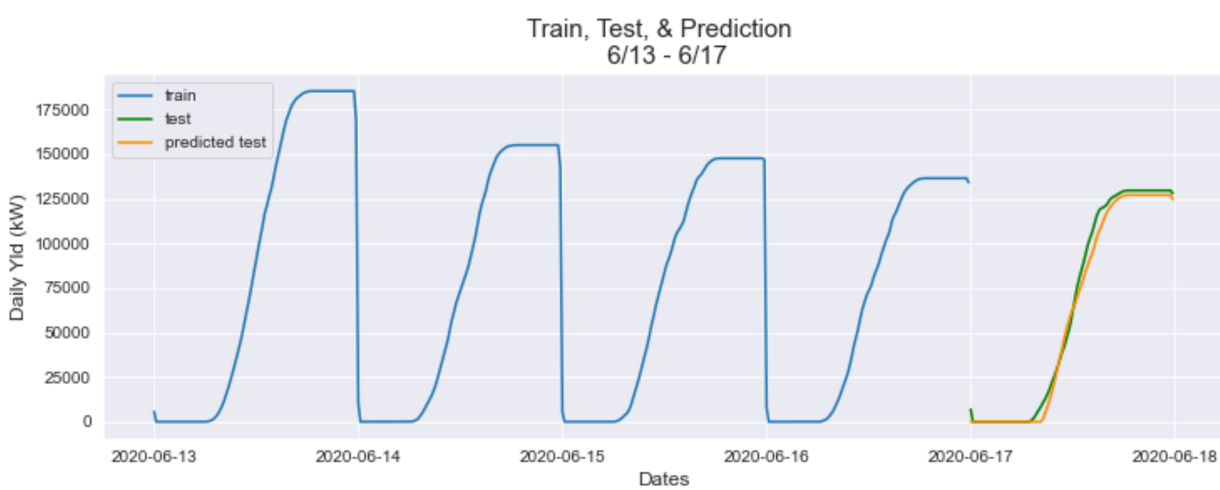
```
SARIMA train R2 Score: 0.984636
```

```
SARIMA test R2 Score: 0.992781
---------------
SARIMA train MAE Score: 1271.469147
SARIMA test MAE Score: 3392.311740
---------------
SARIMA train RMSE Score: 8481.602910
SARIMA test RMSE Score: 4836.309328
---------------

                                      SARIMAX Results
====================================================================
========================
Dep. Variable:                         DAILY_YIELD   No. Observatio
ns:                  384
Model:              SARIMAX(1, 1, 0)x(1, 1, [1], 96)   Log Likelihood
-2401.512
Date:                             Wed, 02 Dec 2020   AIC
4811.024
Time:                                     19:16:53   BIC
4825.662
Sample:                                 06-13-2020   HQIC
4816.891
                                      - 06-16-2020
Covariance Type:                               opg
====================================================================
==========
                 coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------
----------
ar.L1          0.0631      0.010      6.440      0.000       0.044
0.082
ar.S.L96      -0.0396      0.035     -1.123      0.262      -0.109
0.030
ma.S.L96      -0.1692      0.033     -5.100      0.000      -0.234
-0.104
sigma2       1.06e+06    2.1e+04     50.453      0.000    1.02e+06
1.1e+06
====================================================================
===============
Ljung-Box (Q):                       55.11   Jarque-Bera (JB):
45550.01
Prob(Q):                              0.06   Prob(JB):
0.00
Heteroskedasticity (H):               0.77   Skew:
4.84
Prob(H) (two-sided):                  0.21   Kurtosis:
63.95
====================================================================
===============

Warnings:
[1] Covariance matrix calculated using the outer product of gradient
```

```
s (complex-step).
---------------
```







FORECASTING

Fit the model to the entire train/test data:

In [145]:

```
sarima_f_model = SARIMAX(pred_final.DAILY_YIELD,
                         order=(p,d,q),
                         seasonal_order=(P,D,Q,s),
                         freq='15T').fit()
```

```
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:1006: UserWarning: Non-invertible starting sea
sonal moving average Using zeros as starting parameters.
  warn('Non-invertible starting seasonal moving average'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/base
/model.py:567: ConvergenceWarning: Maximum Likelihood optimization f
ailed to converge. Check mle_retvals
  warn("Maximum Likelihood optimization failed to converge. "
```

In [154]:

```
sarima_forecast = sarima_f_model.get_forecast(steps=193).summary_frame()
sarima_forecast
```

Out[154]:

DAILY_YIELD	mean	mean_se	mean_ci_lower	mean_ci_upper
2020-06-18 00:00:00	-240.062415	1136.566162	-2467.691159	1987.566328
2020-06-18 00:15:00	-7278.650324	1658.447592	-10529.147874	-4028.152774
2020-06-18 00:30:00	-7277.625865	2054.242470	-11303.867122	-3251.384608
2020-06-18 00:45:00	-7277.586392	2385.383343	-11952.851834	-2602.320950
2020-06-18 01:00:00	-7277.584594	2675.862055	-12522.177849	-2032.991339
...	...	...	...	...
2020-06-19 23:00:00	119370.674623	24256.803815	71828.212765	166913.136482
2020-06-19 23:15:00	119370.758341	24355.837577	71634.193876	167107.322806
2020-06-19 23:30:00	119373.248201	24454.470272	71443.367207	167303.129195
2020-06-19 23:45:00	117288.213091	24552.706455	69165.792716	165410.633466
2020-06-20 00:00:00	-11267.290953	24743.147071	-59762.968077	37228.386171

193 rows × 4 columns

In [155]:

```
sarima_forecast[sarima_forecast < 0] = 0
sarima_forecast
```

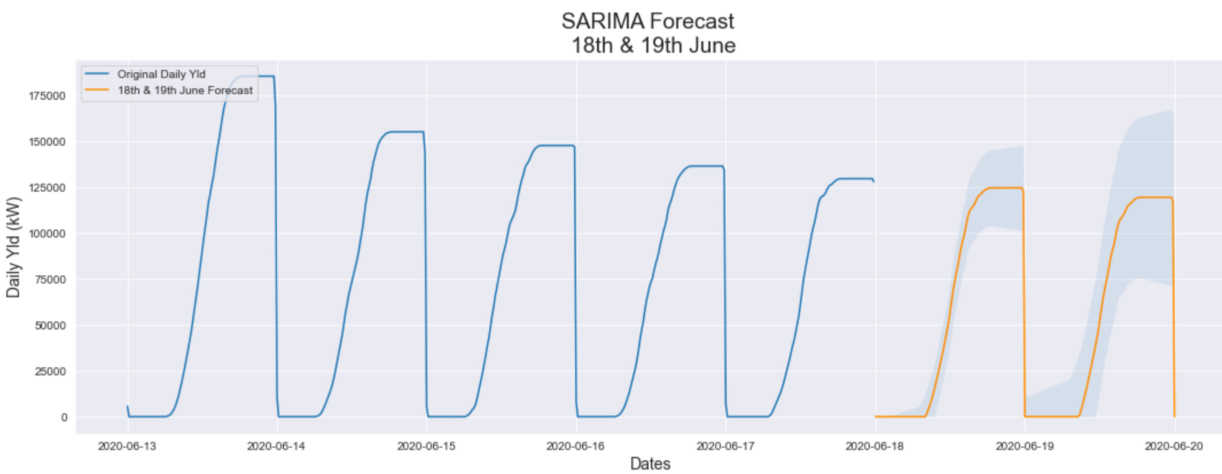
Out[155]:

DAILY_YIELD	mean	mean_se	mean_ci_lower	mean_ci_upper
2020-06-18 00:00:00	0.000000	1136.566162	0.000000	1987.566328
2020-06-18 00:15:00	0.000000	1658.447592	0.000000	0.000000
2020-06-18 00:30:00	0.000000	2054.242470	0.000000	0.000000
2020-06-18 00:45:00	0.000000	2385.383343	0.000000	0.000000
2020-06-18 01:00:00	0.000000	2675.862055	0.000000	0.000000
...	...	...	...	...
2020-06-19 23:00:00	119370.674623	24256.803815	71828.212765	166913.136482
2020-06-19 23:15:00	119370.758341	24355.837577	71634.193876	167107.322806
2020-06-19 23:30:00	119373.248201	24454.470272	71443.367207	167303.129195
2020-06-19 23:45:00	117288.213091	24552.706455	69165.792716	165410.633466
2020-06-20 00:00:00	0.000000	24743.147071	0.000000	37228.386171

193 rows × 4 columns

In [332]:

```
fig, ax = plt.subplots(figsize=(18,6))
ax.plot(pred_final.DAILY_YIELD, label='Original Daily Yld')
ax.plot(sarima_forecast['mean'], label='18th & 19th June Forecast', c='darkorang
e')
ax.fill_between(sarima_forecast.index,
                sarima_forecast.mean_ci_lower, sarima_forecast.mean_ci_upper, al
pha=0.1)

ax.legend(loc='upper left')
ax.set_title('SARIMA Forecast \n 18th & 19th June', size=19)
ax.set_ylabel('Daily Yld (kW)', size=14)
ax.set_xlabel('Dates', size=14);
# plt.savefig('../../data/figures/sarima_forecast.png')
```



In [170]:

```
print('18th Jun Forecasted Output: ',
      round(sarima_forecast[sarima_forecast.index.day == 18]['mean'].max(), 0),
      'kW')

print('19th Jun Forecasted Output: ',
      round(sarima_forecast[sarima_forecast.index.day == 19]['mean'].max(), 0),
      'kW')
```

```
18th Jun Forecasted Output:  124556.0 kW
19th Jun Forecasted Output:  119373.0 kW
```

Modeling 2: FB Prophet

PROPHET is an open source library by Facebook which can be used for time series forecasting. It is more intuitive than SARIMAX, and also faster.

In [264]:

```
prophet_train = train_pred_fin.copy()[['DAILY_YIELD']]
prophet_test = test_pred_fin.copy()[['DAILY_YIELD']]
```

In [265]:

```
# need to have two columns for prophet modeling
# And change their names to ds (datetime) and y (prior datetime data) for prophe
t
# below transforms the index into a column

prophet_train.reset_index(inplace=True)
prophet_train.columns = ['ds', 'y']

prophet_test.reset_index(inplace=True)
prophet_test.columns = ['ds', 'y']
```

In [266]:

```
prophet_train.head()
```

Out[266]:

	ds	y
0	2020-06-13 00:00:00	5683.214286
1	2020-06-13 00:15:00	0.000000
2	2020-06-13 00:30:00	0.000000
3	2020-06-13 00:45:00	0.000000
4	2020-06-13 01:00:00	0.000000

In [267]:

```
prophet_test.head()
```

Out[267]:

	ds	y
0	2020-06-17 00:00:00	6955.232143
1	2020-06-17 00:15:00	0.000000
2	2020-06-17 00:30:00	0.000000
3	2020-06-17 00:45:00	0.000000
4	2020-06-17 01:00:00	0.000000

TRAIN/TEST MODEL, AND IN-SAMPLE PREDICTION

Instantiating model & Fitting model to training data

In [268]:

```
prophet_model = Prophet(daily_seasonality=True,
                        weekly_seasonality=False,
                        yearly_seasonality=False,
                        interval_width=0.95) # confidence interval. Note: entering this did not change any of the performance metric vs the the defaul

prophet_model.fit(prophet_train)
```

I'm going to now make a list of future dates to predict values for. Note that these are the same dates as the prophet_test data index.

In [270]:

```
prophet_future_test_dates = prophet_model.make_future_dataframe(periods=96, freq='15min', include_history=False)
prophet_future_test_dates
```

Out[270]:

	ds
0	2020-06-17 00:00:00
1	2020-06-17 00:15:00
2	2020-06-17 00:30:00
3	2020-06-17 00:45:00
4	2020-06-17 01:00:00
...	...
91	2020-06-17 22:45:00
92	2020-06-17 23:00:00
93	2020-06-17 23:15:00
94	2020-06-17 23:30:00
95	2020-06-17 23:45:00

96 rows × 1 columns

Predicting: I'm going to predict values for the dates we created above. We will then comapre these values to the actual daily yield from our test data.

In [271]:

```
prophet_test_forecast = prophet_model.predict(prophet_future_test_dates)
prophet_test_forecast
```

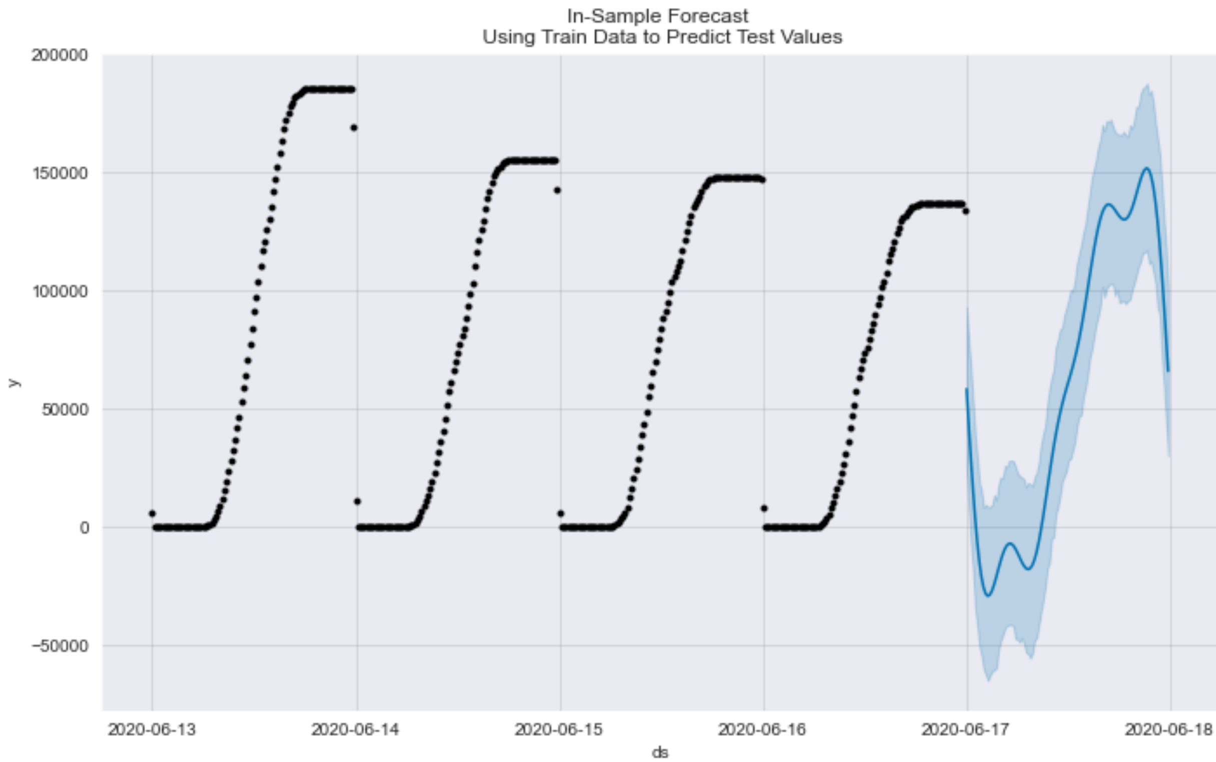
Out[271]:

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additiv
0	2020-06-17 00:00:00	63767.068850	24579.175905	92802.246485	63766.009897	63767.390083	-5609
1	2020-06-17 00:15:00	63689.596914	7929.643029	78372.468096	63680.170035	63697.115274	-20411
2	2020-06-17 00:30:00	63612.124977	-6776.025591	66774.556056	63591.170787	63630.342463	-34598
3	2020-06-17 00:45:00	63534.653041	-18409.708949	53153.843256	63496.407359	63568.874337	-47773
4	2020-06-17 01:00:00	63457.181105	-34414.547999	38833.271145	63401.960367	63507.983835	-59587
...	...	...	...	...	...	...	
91	2020-06-17 22:45:00	56717.122658	89368.574692	157741.771484	52138.066538	61231.455158	62772
92	2020-06-17 23:00:00	56639.650721	72068.985764	145032.131521	51999.001519	61251.930762	51172
93	2020-06-17 23:15:00	56562.178785	59584.668566	130597.262350	51868.723108	61275.658521	38175
94	2020-06-17 23:30:00	56484.706849	45610.642296	118643.387316	51738.600423	61299.386279	24114
95	2020-06-17 23:45:00	56407.234913	30047.848927	100805.018547	51609.794644	61300.050930	9378

96 rows × 16 columns

In [275]:

```
prophet_model.plot(prophet_test_forecast)
plt.title('In-Sample Forecast \n Using Train Data to Predict Test Values');
```



PERFORMANCE METRICS; PLOTTING

I'm going to create a dataframe of just my date_time index, predicted daily yield (yhat), and actual daily yield (y). I will then calculate the performance metrics of my prophet model and plot everything.

In [276]:

```
pred_metric_df = prophet_test_forecast.set_index('ds')[['yhat']].join(prophet_test.set_index('ds').y).reset_index()
pred_metric_df.set_index('ds', inplace=True)
pred_metric_df[pred_metric_df.yhat < 0] = 0
pred_metric_df
```

Out[276]:

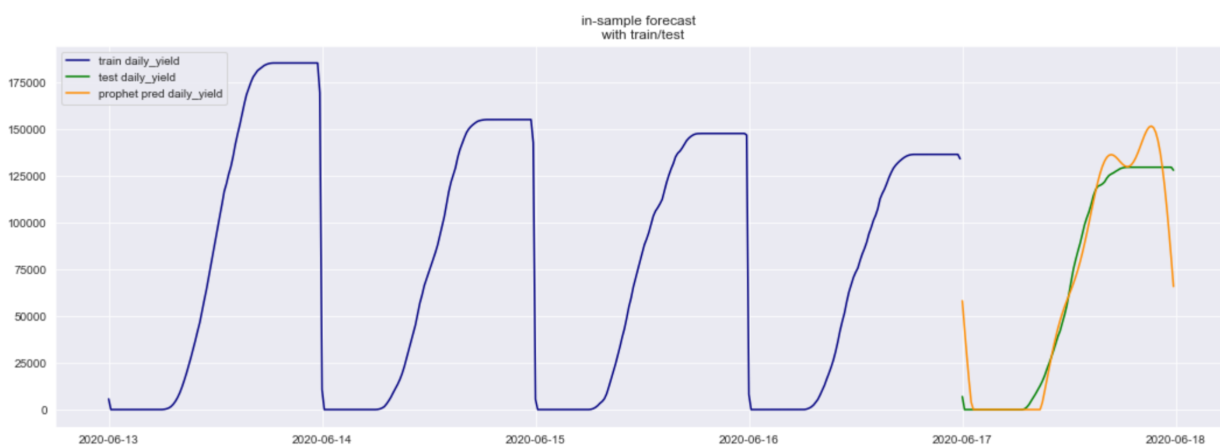
	yhat	y
ds		
2020-06-17 00:00:00	58157.483263	6955.232143
2020-06-17 00:15:00	43277.986849	0.000000
2020-06-17 00:30:00	29013.367322	0.000000
2020-06-17 00:45:00	15761.627529	0.000000
2020-06-17 01:00:00	3869.588867	0.000000
...	...	...
2020-06-17 22:45:00	119489.561615	129571.000000
2020-06-17 23:00:00	107812.235301	129571.000000
2020-06-17 23:15:00	94737.783380	129571.000000
2020-06-17 23:30:00	80599.483645	129571.000000
2020-06-17 23:45:00	65785.665212	127962.767857

96 rows × 2 columns

In [336]:

```
print('Prophet Test R2 Score: %f' % (r2_score(pred_metric_df.y, pred_metric_df.y
hat)))
print('-'*15)

print('Prophet Test MAE Score: %f' % (mean_absolute_error(pred_metric_df.y, pred
_metric_df.yhat)))
print('-'*15)

print('Prophet Test RMSE Score: %f' % (mean_squared_error(pred_metric_df.y, pred
_metric_df.yhat,squared=False)))
print('-'*15)

plt.figure(figsize=(18,6))
plt.plot(prophet_train.ds, prophet_train.y, label='train daily_yield', c='navy')
plt.plot(prophet_test.ds, prophet_test.y, label='test daily_yield', c='green')
plt.plot(pred_metric_df.yhat, label = 'prophet pred daily_yield', color='darkora
nge')
plt.legend(loc='upper left')
plt.title('in-sample forecast \n with train/test');
# plt.savefig('../../data/figures/prophet_pred_model.png')
```

```
Prophet Test R2 Score: 0.941193
---------------
Prophet Test MAE Score: 7681.413889
---------------
Prophet Test RMSE Score: 13927.544700
---------------
```



FORECASTING 2 DAYS

Just like before, I'm going to prepare the dataframe for the prophet model, with isolating and relabeling the date_time index and daily yield column as 'ds' and 'y'

In [282]:

```
prophet_pred_final = pred_final.copy()[['DAILY_YIELD']]
prophet_pred_final.reset_index(inplace=True)
prophet_pred_final.columns = ['ds', 'y']
prophet_pred_final
```

Out[282]:

	ds	y
0	2020-06-13 00:00:00	5683.214286
1	2020-06-13 00:15:00	0.000000
2	2020-06-13 00:30:00	0.000000
3	2020-06-13 00:45:00	0.000000
4	2020-06-13 01:00:00	0.000000
...	...	...
475	2020-06-17 22:45:00	129571.000000
476	2020-06-17 23:00:00	129571.000000
477	2020-06-17 23:15:00	129571.000000
478	2020-06-17 23:30:00	129571.000000
479	2020-06-17 23:45:00	127962.767857

480 rows × 2 columns

I'm going to instantiate and fit the model to the data I prepared above.

In [283]:

```
prophet_model_forecast = Prophet(daily_seasonality=True,
                        weekly_seasonality=False,
                        yearly_seasonality=False,
                        interval_width=0.95)
prophet_model_forecast.fit(prophet_pred_final)
```

Out[283]:

```
<fbprophet.forecaster.Prophet at 0x7fb747e18be0>
```

Just like above, I'm going to create a list of future dates to forecast solar power output against.

In [284]:

```
prophet_forecast_dates = prophet_model_forecast.make_future_dataframe(periods=19
2, include_history=False, freq='15min')
prophet_forecast_dates
```

Out[284]:

	ds
0	2020-06-18 00:00:00
1	2020-06-18 00:15:00
2	2020-06-18 00:30:00
3	2020-06-18 00:45:00
4	2020-06-18 01:00:00
...	...
187	2020-06-19 22:45:00
188	2020-06-19 23:00:00
189	2020-06-19 23:15:00
190	2020-06-19 23:30:00
191	2020-06-19 23:45:00

192 rows × 1 columns

I'm going to use the model above to now forecast solar output. In addtion to that, I'm going to isolate the forecasted values (yhat) and the confidence intervals, so I can plot it.

In [305]:

```
prophet_forecast = prophet_model_forecast.predict(prophet_forecast_dates)
prophet_forecast = prophet_forecast[['ds','yhat_lower','yhat_upper','yhat']]
prophet_forecast.set_index('ds',inplace=True)
prophet_forecast[prophet_forecast < 0] = 0
prophet_forecast
```

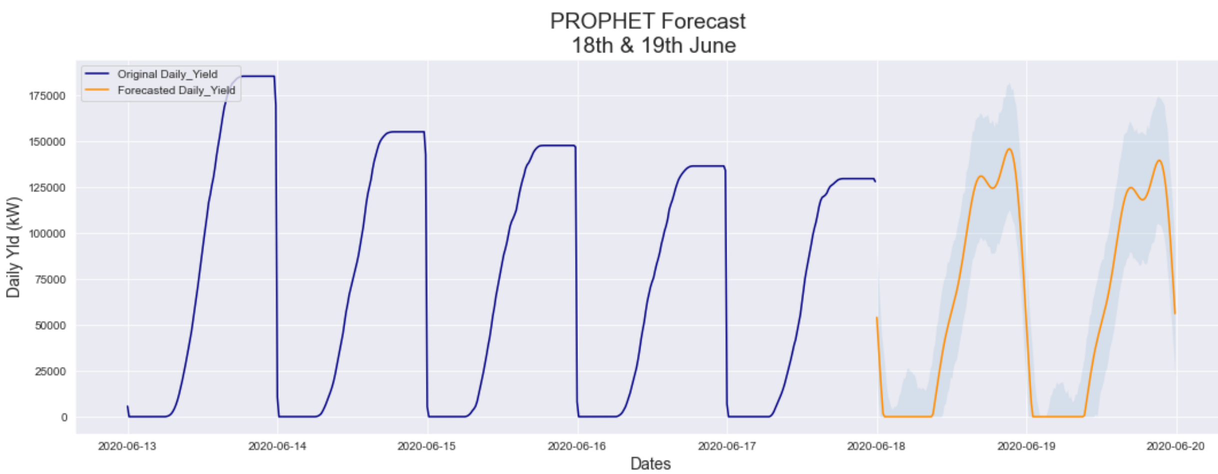
Out[305]:

	yhat_lower	yhat_upper	yhat
ds			
2020-06-18 00:00:00	19642.970926	88677.568945	54061.919557
2020-06-18 00:15:00	6827.558908	75397.866771	39673.304254
2020-06-18 00:30:00	0.000000	59511.630959	25887.823844
2020-06-18 00:45:00	0.000000	44500.807393	13087.847986
2020-06-18 01:00:00	0.000000	36761.040216	1605.952297
...	...	...	...
2020-06-19 22:45:00	70782.319896	141813.624298	108207.942241
2020-06-19 23:00:00	58242.616903	130782.028056	96861.441393
2020-06-19 23:15:00	47943.837339	120160.907106	84173.192763
2020-06-19 23:30:00	35863.996006	108025.785455	70467.292074
2020-06-19 23:45:00	22236.394014	91461.924195	56120.045813

192 rows × 3 columns

In [338]:

```
fig, ax = plt.subplots(figsize=(18,6))
ax.plot(prophet_pred_final.ds, prophet_pred_final.y, label='Original Daily_Yield
', c='navy')
ax.plot(prophet_forecast.index, prophet_forecast.yhat, label = 'Forecasted Daily
_Yield', color='darkorange')
ax.fill_between(prophet_forecast.index,
                prophet_forecast.yhat_lower, prophet_forecast.yhat_upper, alpha=
0.1)
ax.legend(loc='upper left')
ax.set_title('PROPHET Forecast \n 18th & 19th June', size=19)
ax.set_ylabel('Daily Yld (kW)', size=14)
ax.set_xlabel('Dates', size=14);
# plt.savefig('../../data/figures/prophet_forecast.png')
```



In [335]:

```
print('18th Jun Forecasted Output: ',
     round(prophet_forecast[prophet_forecast.index.day == 18]['yhat'].max(), 0),
     'kW')

print('19th Jun Forecasted Output: ',
     round(prophet_forecast[prophet_forecast.index.day == 19]['yhat'].max(), 0),
     'kW')
```

```
18th Jun Forecasted Output:  145849.0 kW
19th Jun Forecasted Output:  139588.0 kW
```

Modeling 3: SARIMAX

This is the same algorithm as SARIMA; the 'X' here stands for exogenous. These are variables, which in my case here is the ambient temperature, we can add in addition to the endogenous variable, or the main feature which in my case is the daily yield, to help the model predict and forecast better.

In [197]:

```
train_sarimax = train_pred_fin[['DAILY_YIELD']]
test_sarimax = test_pred_fin[['DAILY_YIELD']]

# Exogenous Variable (Ambient Temperature)
train_sarimax_exog = train_pred_fin[['AMBIENT_TEMPERATURE']]
test_sarimax_exog = test_pred_fin[['AMBIENT_TEMPERATURE']]
```

In [193]:

```
train_sarimax.head()
```

Out[193]:

	DAILY_YIELD
DATE_TIME	
2020-06-13 00:00:00	5683.214286
2020-06-13 00:15:00	0.000000
2020-06-13 00:30:00	0.000000
2020-06-13 00:45:00	0.000000
2020-06-13 01:00:00	0.000000

In [194]:

```
train_sarimax_exog.head()
```

Out[194]:

	AMBIENT_TEMPERATURE
DATE_TIME	
2020-06-13 00:00:00	21.771613
2020-06-13 00:15:00	21.730046
2020-06-13 00:30:00	21.687068
2020-06-13 00:45:00	21.619232
2020-06-13 01:00:00	21.625968

In [195]:

```
test_sarimax.head()
```

Out[195]:

	DAILY_YIELD
DATE_TIME	
2020-06-17 00:00:00	6955.232143
2020-06-17 00:15:00	0.000000
2020-06-17 00:30:00	0.000000
2020-06-17 00:45:00	0.000000
2020-06-17 01:00:00	0.000000

In [198]:

```
test_sarimax_exog.head()
```

Out[198]:

	AMBIENT_TEMPERATURE
DATE_TIME	
2020-06-17 00:00:00	22.895672
2020-06-17 00:15:00	22.868416
2020-06-17 00:30:00	22.826764
2020-06-17 00:45:00	22.795615
2020-06-17 01:00:00	22.771452

AUTO-ARIMA

--> **ENTER EXPLANATION AIC (since that is what we're minimizing here)** <--

In [189]:

```
auto_arima(train_sarimax,
           exogenous=train_sarimax_exog,
           start_p=0,d=1,start_q=0,
           max_p=4,max_d=4,max_q=4,
           start_P=0,D=1,start_Q=0,
           max_P=1,max_D=1,max_Q=1,m=96,
           seasonal=True,
           error_action='warn',trace=True,
           supress_warning=True,stepwise=True,
           random_state=20,n_fits=1)
```

```
Performing stepwise search to minimize aic

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'

 ARIMA(0,1,0)(0,1,0)[96]             : AIC=5087.452, Time=11.62 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'

 ARIMA(1,1,0)(1,1,0)[96]             : AIC=4787.500, Time=52.33 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(0,1,1)(0,1,1)[96]             : AIC=4866.556, Time=17.19 sec
```

```
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'

 ARIMA(1,1,0)(0,1,0)[96]             : AIC=5071.438, Time=2.47 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(1,1,0)(1,1,1)[96]             : AIC=4764.205, Time=76.24 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(1,1,0)(0,1,1)[96]             : AIC=4865.263, Time=17.87 sec
```

```
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(0,1,0)(1,1,1)[96]             : AIC=4910.129, Time=29.99 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(2,1,0)(1,1,1)[96]             : AIC=4766.203, Time=88.44 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(1,1,1)(1,1,1)[96]             : AIC=4869.406, Time=80.01 sec
```

```
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(0,1,1)(1,1,1)[96]             : AIC=4764.404, Time=70.14 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:963: UserWarning: Non-stationary starting auto
regressive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:975: UserWarning: Non-invertible starting MA p
arameters found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'

 ARIMA(2,1,1)(1,1,1)[96]             : AIC=4870.545, Time=46.58 sec

/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:866: UserWarning: Too few observations to esti
mate starting parameters for seasonal ARMA. All parameters except fo
r variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
```

```
 ARIMA(1,1,0)(1,1,1)[96] intercept   : AIC=4765.554, Time=93.48 sec

Best model:  ARIMA(1,1,0)(1,1,1)[96]
Total fit time: 586.640 seconds
```

Out[189]:

```
ARIMA(order=(1, 1, 0), scoring_args={}, seasonal_order=(1, 1, 1, 96)
,
      with_intercept=False)
```

TRAIN/TEST MODEL, AND IN-SAMPLE PREDICTION

FITTING MODEL TO TRAIN DATA

In [207]:

```
p,d,q = [1,1,0]
P,D,Q,s = [1,1,1,96]

sarimax_model = SARIMAX(endog=train_sarimax,
                        exog=train_sarimax_exog,
                        order=(p,d,q),
                        seasonal_order=(P,D,Q,s),
                        freq='15T').fit()
```

```
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
```

MAKING PREDICTIONS AGAINST TRAIN AND TEST DATA (y_hats)

In [209]:

```
train_sarimax_y_hat = pd.DataFrame(sarimax_model.predict(typ='levels'), columns=
['pred_daily_yld'])

test_sarimax_y_hat = pd.DataFrame(sarimax_model.predict(start=test_sarimax.index
[0],
                                                         end=test_sarimax.index[-
1],
                                                         exog=test_sarimax_exog,
                                                         typ='levels'), columns=[
'pred_daily_yld'])

# zero out negative predictions:
train_sarimax_y_hat[train_sarimax_y_hat < 0] = 0

test_sarimax_y_hat[test_sarimax_y_hat < 0] = 0
```

In [210]:

```
train_sarimax_y_hat.head()
```

Out[210]:

	pred_daily_yld
2020-06-13 00:00:00	20449.352895
2020-06-13 00:15:00	5291.924688
2020-06-13 00:30:00	0.000000
2020-06-13 00:45:00	0.000000
2020-06-13 01:00:00	8.365063

In [211]:

```
test_sarimax_y_hat.head()
```

Out[211]:

	pred_daily_yld
2020-06-17 00:00:00	0.0
2020-06-17 00:15:00	0.0
2020-06-17 00:30:00	0.0
2020-06-17 00:45:00	0.0
2020-06-17 01:00:00	0.0

PERFORMANCE METRICS; PLOTTING

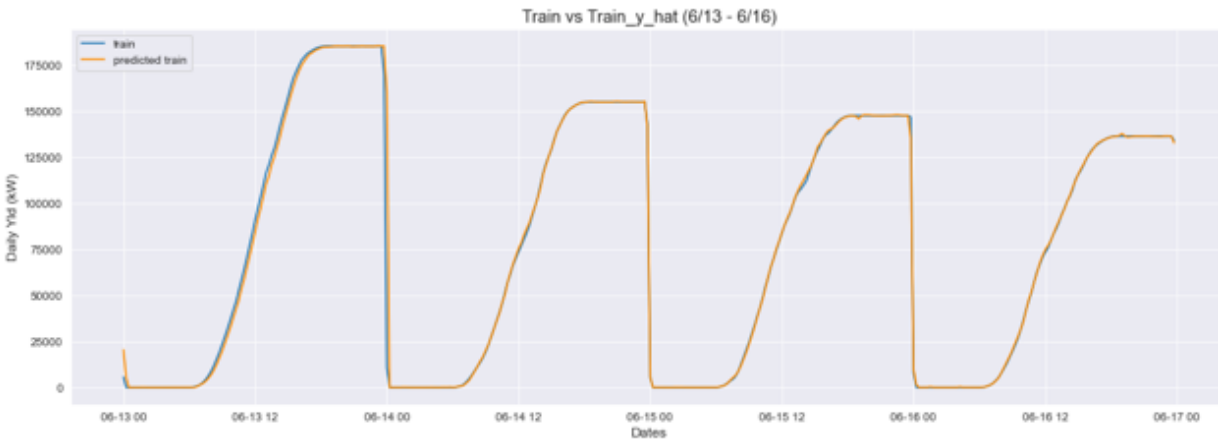
In [340]:

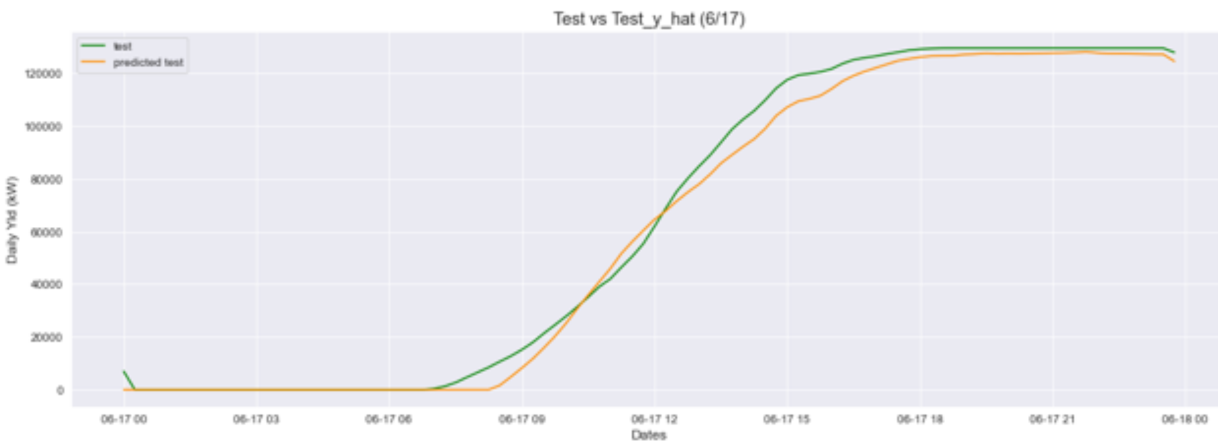
```
print('SARIMAX train R2 Score: %f' % (r2_score(train_sarimax.DAILY_YIELD,
                                             train_sarimax_y_hat.pred_daily_yld
)))
print('SARIMAX test R2 Score: %f' % (r2_score(test_sarimax.DAILY_YIELD,
                                             test_sarimax_y_hat.pred_daily_yld)
))

print('-'*15)

print('SARIMAX train MAE Score: %f' % (mean_absolute_error(train_sarimax.DAILY_Y
IELD,
                                                         train_sarimax_y_hat.pr
ed_daily_yld)))
print('SARIMAX test MAE Score: %f' % (mean_absolute_error(test_sarimax.DAILY_YIE
LD,
```

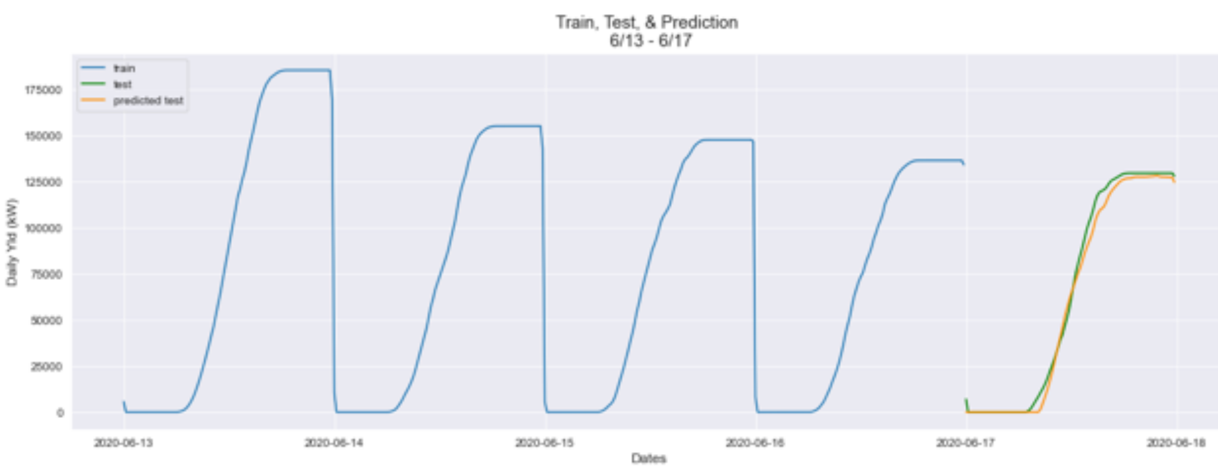
```
                                                         test_sarimax_y_hat.pre
d_daily_yld)))

print('-'*15)

print('SARIMAX train RMSE Score: %f' % (mean_squared_error(train_sarimax.DAILY_Y
IELD,
                                                         train_sarimax_y_hat.pr
ed_daily_yld,
                                                         squared=False)))
print('SARIMAX test RMSE Score: %f' % (mean_squared_error(test_sarimax.DAILY_YIE
LD,
                                                         test_sarimax_y_hat.pre
d_daily_yld,
                                                         squared=False)))

print('-'*15, '\n')

print(sarimax_model.summary())

print('-'*15)

fig, ax1 = plt.subplots(figsize=(18,6))
ax1.plot(train_sarimax, label='train')
ax1.plot(train_sarimax_y_hat, label='predicted train', c='darkorange')
ax1.legend(loc='upper left')
ax1.set_title('Train vs Train_y_hat (6/13 - 6/16)', size=15)
ax1.set_ylabel('Daily Yld (kW)', size=12)
ax1.set_xlabel('Dates', size=12)

fig, ax2 = plt.subplots(figsize=(18,6))
ax2.plot(test_sarimax, label='test', c='g')
ax2.plot(test_sarimax_y_hat, label='predicted test', c='darkorange')
ax2.legend(loc='upper left')
ax2.set_title('Test vs Test_y_hat (6/17)', size=15)
ax2.set_ylabel('Daily Yld (kW)', size=12)
ax2.set_xlabel('Dates', size=12)

fig, ax3 = plt.subplots(figsize=(18,6))
ax3.plot(train_sarimax, label='train')
ax3.plot(test_sarimax, label='test', c='g')
ax3.plot(test_sarimax_y_hat, label='predicted test', c='darkorange')
ax3.legend(loc='upper left')
ax3.set_title('Train, Test, & Prediction \n 6/13 - 6/17', size=15)
ax3.set_ylabel('Daily Yld (kW)', size=12)
ax3.set_xlabel('Dates', size=12);
# plt.savefig('../../data/figures/sarimax_pred.png')
```

```
SARIMAX train R2 Score: 0.986672
SARIMAX test R2 Score: 0.993385
---------------
SARIMAX train MAE Score: 1244.521925
SARIMAX test MAE Score: 3282.352611
---------------
```

```
SARIMAX train RMSE Score: 7899.641976
SARIMAX test RMSE Score: 4629.702527
---------------

                                      SARIMAX Results
====================================================================
========================
Dep. Variable:                            DAILY_YIELD   No. Observatio
ns:                    384
Model:             SARIMAX(1, 1, 0)x(1, 1, [1], 96)   Log Likelihood
-2377.102
Date:                                Wed, 02 Dec 2020   AIC
4764.205
Time:                                        20:20:45   BIC
4782.502
Sample:                                    06-13-2020   HQIC
4771.538
                                         - 06-16-2020
Covariance Type:                                  opg
====================================================================
===================
                          coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------
-------------------
AMBIENT_TEMPERATURE   939.2668    116.636      8.053      0.000
710.664    1167.869
ar.L1                   0.0741      0.009      8.407      0.000
0.057      0.091
ar.S.L96               -0.0120      0.034     -0.354      0.723
-0.078       0.054
ma.S.L96               -0.2235      0.025     -8.994      0.000
-0.272      -0.175
sigma2               8.951e+05   1.57e+04     57.155      0.000    8
.64e+05    9.26e+05
====================================================================
===============
Ljung-Box (Q):                        47.49   Jarque-Bera (JB):
80945.48
Prob(Q):                               0.19   Prob(JB):
0.00
Heteroskedasticity (H):                0.80   Skew:
6.47
Prob(H) (two-sided):                   0.27   Kurtosis:
84.25
====================================================================
===============

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







RETRIEVING HISTORICAL WEATHER DATA- FOR FORECASTING

In [232]:

```
resp = requests.get('https://weather.visualcrossing.com/VisualCrossingWebService
s/rest/services/weatherdata/history?aggregateHours=0&aggregateMinutes=15&combina
tionMethod=aggregate&startDateTime=2020-06-17T00%3A00%3A00&endDateTime=2020-06-2
2T00%3A00%3A00&maxStations=-1&maxDistance=-1&contentType=json&unitGroup=metric&l
ocationMode=array&key=W9LFIRDB34JXS3E2KUHGX3RD9&dataElements=default&locations=N
ashik%2C%20India')
forecast_wthr_data_all = pd.DataFrame.from_dict(resp.json()['locations'][0]['val
ues'])
forecast_wthr_data_all.head()
```

Out[232]:

	temp	maxt	visibility	wspd	datetimeStr	heatindex	cloudcover	mint	datetim
0	NaN	NaN	NaN	NaN	2020-06-17T00:00:00+05:30	NaN	NaN	NaN	159235200000
1	NaN	NaN	NaN	NaN	2020-06-17T00:15:00+05:30	NaN	NaN	NaN	159235290000
2	NaN	NaN	NaN	NaN	2020-06-17T00:30:00+05:30	NaN	NaN	NaN	159235380000
3	NaN	NaN	NaN	NaN	2020-06-17T00:45:00+05:30	NaN	NaN	NaN	159235470000
4	NaN	NaN	NaN	NaN	2020-06-17T01:00:00+05:30	NaN	NaN	NaN	159235560000

In [233]:

```python
# removing '+05:30' from the string date time column

forecast_wthr_data_all.datetimeStr = forecast_wthr_data_all.datetimeStr.map(lamb
da x: x[:-6])


# changing date time column to datetime object, and then setting it as index

forecast_wthr_data_all.datetimeStr = pd.to_datetime(forecast_wthr_data_all.datet
imeStr, infer_datetime_format=True)
forecast_wthr_data_all.set_index('datetimeStr', inplace=True)
forecast_wthr_data_all.head()
```

Out[233]:

	temp	maxt	visibility	wspd	heatindex	cloudcover	mint	datetime	precip
datetimeStr									
2020-06-17 00:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1592352000000	0.0
2020-06-17 00:15:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1592352900000	0.0
2020-06-17 00:30:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1592353800000	0.0
2020-06-17 00:45:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1592354700000	0.0
2020-06-17 01:00:00	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1592355600000	0.0

In [234]:

```
# Isolate temperature data

forecast_wthr_temp = forecast_wthr_data_all[['temp']]
forecast_wthr_temp.head()
```

Out[234]:

	temp
datetimeStr	
2020-06-17 00:00:00	NaN
2020-06-17 00:15:00	NaN
2020-06-17 00:30:00	NaN
2020-06-17 00:45:00	NaN
2020-06-17 01:00:00	NaN

In [235]:

```
# checking for amount of nans

forecast_wthr_temp.isna().sum()
```

Out[235]:

```
temp    229
dtype: int64
```

In [236]:

```
# interpolate

forecast_wthr_temp.interpolate(inplace=True)
forecast_wthr_temp
```

```
<ipython-input-236-8f891af3e272>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pand
as-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
py
  forecast_wthr_temp.interpolate(inplace=True)
```

Out[236]:

	temp
datetimeStr	
2020-06-17 00:00:00	NaN
2020-06-17 00:15:00	NaN
2020-06-17 00:30:00	NaN
2020-06-17 00:45:00	NaN
2020-06-17 01:00:00	NaN
...	...
2020-06-21 22:15:00	23.1
2020-06-21 22:30:00	23.1
2020-06-21 22:45:00	23.1
2020-06-21 23:00:00	23.1
2020-06-21 23:15:00	24.2

478 rows × 1 columns

In [237]:

```
# Isolate historical temp data for forecasting period (6/18 and 6/19)

forecast_wthr_temp = forecast_wthr_temp[(forecast_wthr_temp.index >= '2020-06-18
00:00:00') & (forecast_wthr_temp.index <= '2020-06-20 00:00:00')]
forecast_wthr_temp
```

Out[237]:

	temp
datetimeStr	
2020-06-18 00:00:00	24.609091
2020-06-18 00:15:00	24.563636
2020-06-18 00:30:00	24.518182
2020-06-18 00:45:00	24.472727
2020-06-18 01:00:00	24.427273
...	...
2020-06-19 23:00:00	25.645455
2020-06-19 23:15:00	25.600000
2020-06-19 23:30:00	25.600000
2020-06-19 23:45:00	25.554545
2020-06-20 00:00:00	25.509091

193 rows × 1 columns

FORECASTING

Fit the model to the entire train/test data:

In [239]:

```
sarimax_f_model = SARIMAX(endog=pred_final.DAILY_YIELD,
                          exog=pred_final.AMBIENT_TEMPERATURE,
                          order=(p,d,q),
                          seasonal_order=(P,D,Q,s),
                          freq='15T').fit()
```

```
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
base/tsa_model.py:159: ValueWarning: No frequency information was pr
ovided, so inferred frequency 15T will be used.
  warnings.warn('No frequency information was'
/Users/oz/opt/anaconda3/lib/python3.8/site-packages/statsmodels/tsa/
statespace/sarimax.py:1006: UserWarning: Non-invertible starting sea
sonal moving average Using zeros as starting parameters.
  warn('Non-invertible starting seasonal moving average'
```

Get Forecast- 2 days ahead

In [241]:

```
sarimax_forecast = sarimax_f_model.get_forecast(steps=193, exog=forecast_wthr_te
mp).summary_frame()
sarimax_forecast
```

Out[241]:

DAILY_YIELD	mean	mean_se	mean_ci_lower	mean_ci_upper
2020-06-18 00:00:00	2900.877472	1513.535719	-65.598027	5867.352970
2020-06-18 00:15:00	-4115.861118	2203.376783	-8434.400257	202.678020
2020-06-18 00:30:00	-4108.961410	2726.769316	-9453.331064	1235.408244
2020-06-18 00:45:00	-4117.784166	3164.904513	-10320.883025	2085.314694
2020-06-18 01:00:00	-4138.134078	3549.369693	-11094.770844	2818.502689
...	...	...	...	...
2020-06-19 23:00:00	124902.771096	32275.700700	61643.560149	188161.982043
2020-06-19 23:15:00	124957.950535	32407.805039	61439.819841	188476.081230
2020-06-19 23:30:00	124991.943048	32539.373050	61215.943790	188767.942305
2020-06-19 23:45:00	122929.699314	32670.410892	58896.870606	186962.528021
2020-06-20 00:00:00	-5376.503635	32926.083679	-69910.441798	59157.434529

193 rows × 4 columns

In [247]:

```
# zero out negative predictions

sarimax_forecast[sarimax_forecast < 0] = 0
sarimax_forecast
```

Out[247]:

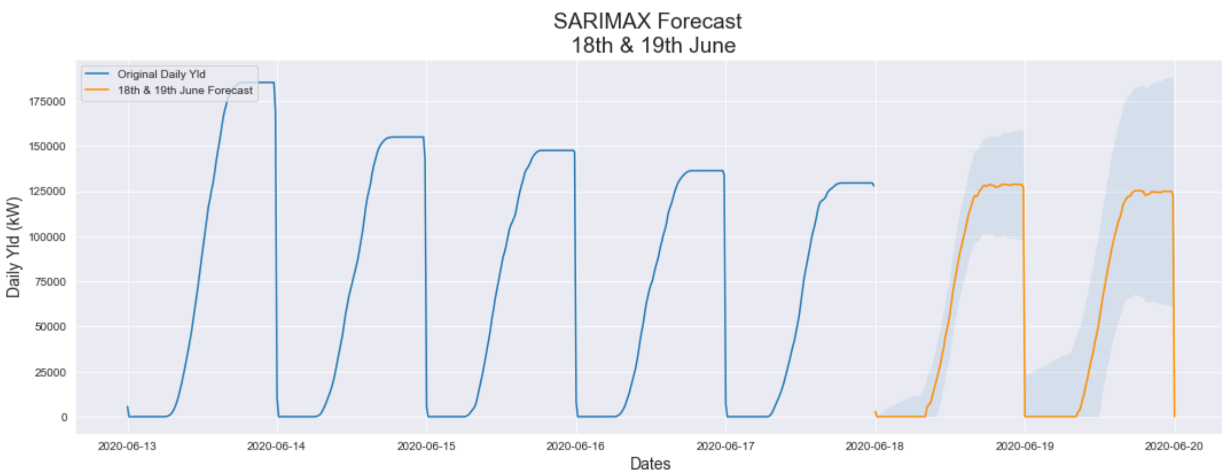
DAILY_YIELD	mean	mean_se	mean_ci_lower	mean_ci_upper
2020-06-18 00:00:00	2900.877472	1513.535719	0.000000	5867.352970
2020-06-18 00:15:00	0.000000	2203.376783	0.000000	202.678020
2020-06-18 00:30:00	0.000000	2726.769316	0.000000	1235.408244
2020-06-18 00:45:00	0.000000	3164.904513	0.000000	2085.314694
2020-06-18 01:00:00	0.000000	3549.369693	0.000000	2818.502689
...	...	...	...	...
2020-06-19 23:00:00	124902.771096	32275.700700	61643.560149	188161.982043
2020-06-19 23:15:00	124957.950535	32407.805039	61439.819841	188476.081230
2020-06-19 23:30:00	124991.943048	32539.373050	61215.943790	188767.942305
2020-06-19 23:45:00	122929.699314	32670.410892	58896.870606	186962.528021
2020-06-20 00:00:00	0.000000	32926.083679	0.000000	59157.434529

193 rows × 4 columns

Plotting

In [341]:

```
fig, ax = plt.subplots(figsize=(18,6))
ax.plot(pred_final.DAILY_YIELD, label='Original Daily Yld')
ax.plot(sarimax_forecast['mean'], label='18th & 19th June Forecast', c='darkoran
ge')
ax.fill_between(sarimax_forecast.index,
                sarimax_forecast.mean_ci_lower, sarimax_forecast.mean_ci_upper,
alpha=0.1)

ax.legend(loc='upper left')
ax.set_title('SARIMAX Forecast \n 18th & 19th June', size=19)
ax.set_ylabel('Daily Yld (kW)', size=14)
ax.set_xlabel('Dates', size=14);
# plt.savefig('../../data/figures/sarimax_forecast.png')
```



In [249]:

```
print('18th Jun Forecasted Output: ',
     round(sarimax_forecast[sarimax_forecast.index.day == 18]['mean'].max(), 0),
     'kW')

print('19th Jun Forecasted Output: ',
     round(sarimax_forecast[sarimax_forecast.index.day == 19]['mean'].max(), 0),
     'kW')
```

```
18th Jun Forecasted Output:  128946.0 kW
19th Jun Forecasted Output:  125548.0 kW
```

In [ ]: