The Problem:

Wind energy relies on a variable power source, the wind! I wanted to see if we could build a model to predict future wind power based on how much wind had been recorded in the past. I used the datasource identified below.

[https://www.kaggle.com/berkerisen/wind-turbine-scada-dataset (https://www.kaggle.com/berkerisen/wind-turbine-scada-dataset)](https://www.kaggle.com/berkerisen/wind-turbine-scada-dataset)

Context

In Wind Turbines, Scada Systems measure and save data's like wind speed, wind direction, generated power etc. for 10 minutes intervals. This file was taken from a wind turbine's scada system that is working and generating power in Turkey. Content The data's in the file are: • Date/Time (for 10 minutes intervals) • LV ActivePower (kW): The power generated by the turbine for that moment • Wind Speed (m/s): The wind speed at the hub height of the turbine (the wind speed that turbine use for electricity generation) • TheoreticalPowerCurve (KWh): The theoretical power values that the turbine generates with that wind speed which is given by the turbine manufacturer • Wind Direction (°): The wind direction at the hub height of the turbine (wind turbines turn to this direction automaticly)

My Approach:

My plan was to build 2 time series models with an ARIMA model and Facebook's Prophet Package in order to see if I can predict wind speed. I decided to test a number of different parameters in the ARIMA Model in order to seee which AR term, which MA term, and the number of differencing required to make the time series stationary. In order to implement an ARIMA model, I would have to make the data stationary in order to determine the best parameters, but then I will have the reverse that proces in order to implement my findings in an actual forecast.

I will need to determine:

1) What is the timeframe I should be forecasting? 2) How much historical data should I use? 3) What are the seasonal patterns? 4) How much autocorrelation is there?

What are the next steps?

1. Sourcing and Loading

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf
from statsmodels.tsa.stattools import adfuller
```

In [2]:
```
#!pip install watermark

#once it is installed, you'll just need this in the future notebook
%load_ext watermark
```

In [3]:
```
%watermark -d -t -v -p numpy,pandas -g
```

```
2020-12-04 12:03:27

CPython 3.7.6
IPython 7.12.0

numpy 1.18.1
pandas 1.1.4
Git hash:
```

In [4]:
```
winddata = pd.read_csv("Data/T1.csv")
```

2. Data Transformation.

We have too many datapoint, so I want to restrict our data to only one month of data (July), and I will change the measurements to every hour as opposed to every 10 minutes

In [5]:
```
winddata.shape
```

Out[5]:
```
(50530, 5)
```

In [6]:
```
winddata.dtypes
```

Out[6]:
```
Date/Time                          object
LV ActivePower (kW)               float64
Wind Speed (m/s)                  float64
Theoretical_Power_Curve (KWh)     float64
Wind Direction (°)                float64
dtype: object
```

In [7]:
```
winddata.head()
```

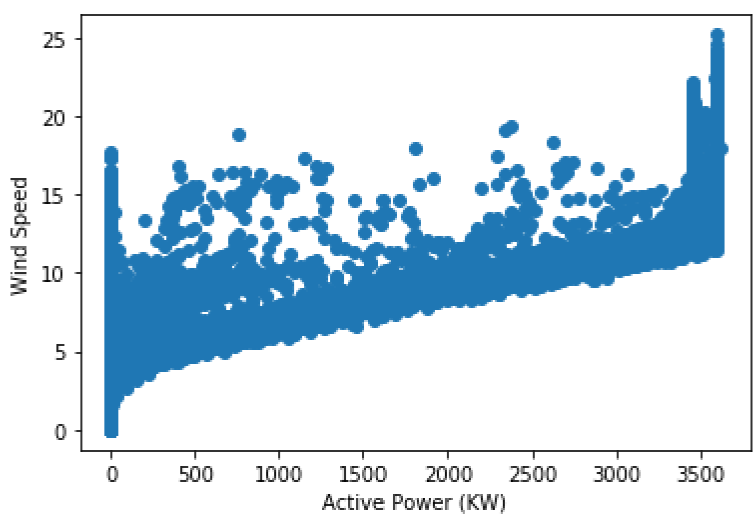
Out[7]:

	Date/Time	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical_Power_Curve (KWh)	Wind Direction (°)
0	01 01 2018 00:00	380.047791	5.311336	416.328908	259.994904
1	01 01 2018 00:10	453.769196	5.672167	519.917511	268.641113
2	01 01 2018 00:20	306.376587	5.216037	390.900016	272.564789
3	01 01 2018 00:30	419.645905	5.659674	516.127569	271.258087
4	01 01 2018 00:40	380.650696	5.577941	491.702972	265.674286

Speed vs Power

Intersting to see the correlation here. It shows that the wind speed is much more variable, but that generally speaking that there is a slowly building power increase of power with wind speed, but at the same time, bursts of wind are leading to more active power.

In [8]:
```
plt.scatter(winddata['LV ActivePower (kW)'], winddata['Wind Speed (m/s)'])

plt.xlabel("Active Power (KW)")
plt.ylabel("Wind Speed")

plt.show()
```

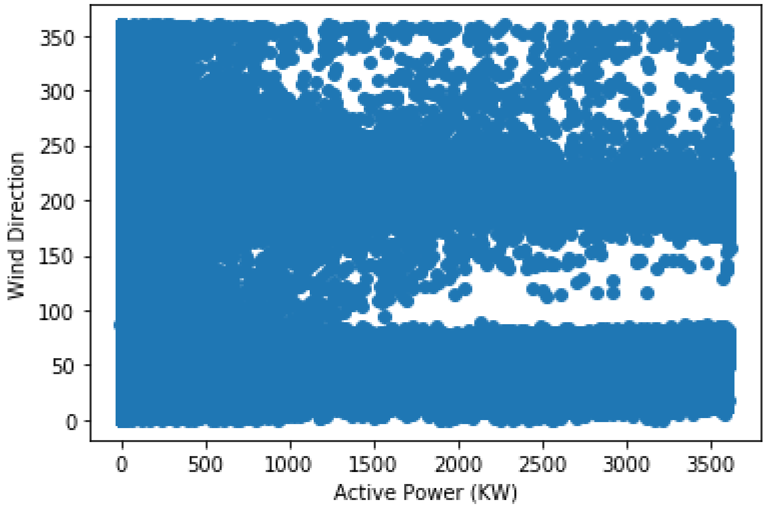


In [9]:
```
correlatoin = winddata['LV ActivePower (kW)'].corr(winddata['Wind Speed (m/s)'])

print("Correlation is:", correlatoin)
```

```
Correlation is: 0.9127742911275553
```

Luckily there is no correlation between wind direction and active power, so we don't need to analyze wind direction. This is because the wind turbine adjusts to the direction of the wind.

In [10]:
```
plt.scatter(winddata['LV ActivePower (kW)'], winddata['Wind Direction (°)'])

plt.xlabel("Active Power (KW)")
plt.ylabel("Wind Direction")

plt.show()
```



In [11]:
```
winddata.isnull().values.any()
winddata.isnull().sum()
```

Out[11]:
```
Date/Time                        0
LV ActivePower (kW)              0
Wind Speed (m/s)                 0
Theoretical_Power_Curve (KWh)    0
Wind Direction (°)               0
dtype: int64
```

In [12]:
```
winddata.set_index('Date/Time', inplace = True)
```

In [13]:
```
winddata.index = pd.to_datetime(winddata.index)
```

In [14]:
```
winddata.index.dtype
```

Out[14]:
```
dtype('<M8[ns]')
```

In [15]:
```
winddata.head()
```

Out[15]:

	LV ActivePower (kW)	Wind Speed (m/s)	Theoretical_Power_Curve (KWh)	Wind Direction (°)
Date/Time				
2018-01-01 00:00:00	380.047791	5.311336	416.328908	259.994904
2018-01-01 00:10:00	453.769196	5.672167	519.917511	268.641113
2018-01-01 00:20:00	306.376587	5.216037	390.900016	272.564789
2018-01-01 00:30:00	419.645905	5.659674	516.127569	271.258087
2018-01-01 00:40:00	380.650696	5.577941	491.702972	265.674286

In [16]:
```
len(winddata)
```

Out[16]: 50530

How do I get this data to resample by hour?

In [17]:
```
windspeed = winddata['Wind Speed (m/s)']
```

In [18]:
```
resampled = windspeed.resample('1H').mean()
```

In [19]:
```
summarydata1 = winddata.between_time('0:05', '0:15')
summarydata2 = winddata.between_time('1:05', '1:15')
summarydata3 = winddata.between_time('2:05', '2:15')
summarydata4 = winddata.between_time('3:05', '3:15')
summarydata5 = winddata.between_time('4:05', '4:15')
summarydata6 = winddata.between_time('5:05', '5:15')
summarydata7 = winddata.between_time('6:05', '6:15')
summarydata8 = winddata.between_time('7:05', '7:15')
summarydata9 = winddata.between_time('8:05', '8:15')
summarydata10 = winddata.between_time('9:05', '9:15')
summarydata11 = winddata.between_time('10:05', '10:15')
summarydata12 = winddata.between_time('11:05', '11:15')
summarydata13 = winddata.between_time('12:05', '12:15')
summarydata14 = winddata.between_time('13:05', '13:15')
summarydata15 = winddata.between_time('14:05', '14:15')
summarydata16 = winddata.between_time('15:05', '15:15')
summarydata17 = winddata.between_time('16:05', '16:15')
summarydata18 = winddata.between_time('17:05', '17:15')
summarydata19 = winddata.between_time('18:05', '18:15')
summarydata20 = winddata.between_time('19:05', '19:15')
summarydata21 = winddata.between_time('20:05', '20:15')
summarydata22 = winddata.between_time('21:05', '21:15')
summarydata23 = winddata.between_time('22:05', '22:15')
```

In [20]:
```
summary = pd.concat([summarydata1,summarydata2,summarydata3,summarydata4,summaryd
len(summary)
```

Out[20]: 8073

In [21]:
```
#summary = summary.sort_values(by='Date/Time')
summary.sort_index(inplace=True)
```

In [22]:
```
len(summary)
```

Out[22]: 8073

In [23]:
```
len(resampled)
```

Out[23]: 8760

In [24]:
```
print(resampled)
```

```
Date/Time
2018-01-01 00:00:00     5.506868
2018-01-01 01:00:00     5.644205
2018-01-01 02:00:00     6.452037
2018-01-01 03:00:00     6.811455
2018-01-01 04:00:00     7.748749
                          ...
2018-12-31 19:00:00     6.481788
2018-12-31 20:00:00     8.083644
2018-12-31 21:00:00     9.121862
2018-12-31 22:00:00    11.340147
2018-12-31 23:00:00     9.855317
Freq: H, Name: Wind Speed (m/s), Length: 8760, dtype: float64
```

Here we make a predictor variable, y, but then I change it to be called "july".

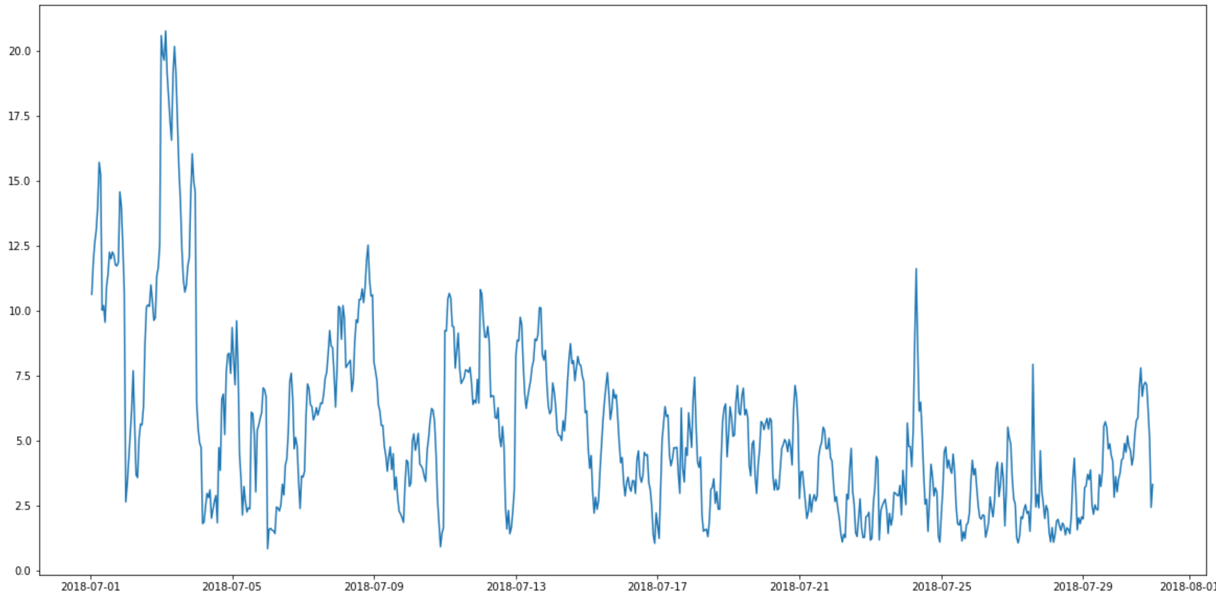
In [25]:
```
m1 = resampled.index > '2018-07-01'
m2 = resampled.index < '2018-07-31'
m3 = resampled.index < '2018-08-09'
july = resampled[np.logical_and.reduce([m1, m2])]
Julyaug =  resampled[np.logical_and.reduce([m1, m3])]
Julyaug_log = np.log(Julyaug)
print(july)
```

```
Date/Time
2018-07-01 01:00:00    10.626840
2018-07-01 02:00:00    11.841422
2018-07-01 03:00:00    12.611197
2018-07-01 04:00:00    13.076755
2018-07-01 05:00:00    13.984995
                          ...
2018-07-30 19:00:00     7.141817
2018-07-30 20:00:00     6.158737
2018-07-30 21:00:00     5.030241
2018-07-30 22:00:00     2.439380
2018-07-30 23:00:00     3.318539
Freq: H, Name: Wind Speed (m/s), Length: 719, dtype: float64
```

3. Plotting the independent variable.

In [26]:
```
plt.figure(figsize=(20,10))

plt.plot(july)
```

Out[26]:
```
[<matplotlib.lines.Line2D at 0x2a960e89f88>]
```



In [27]:
```
print(len(july))
```

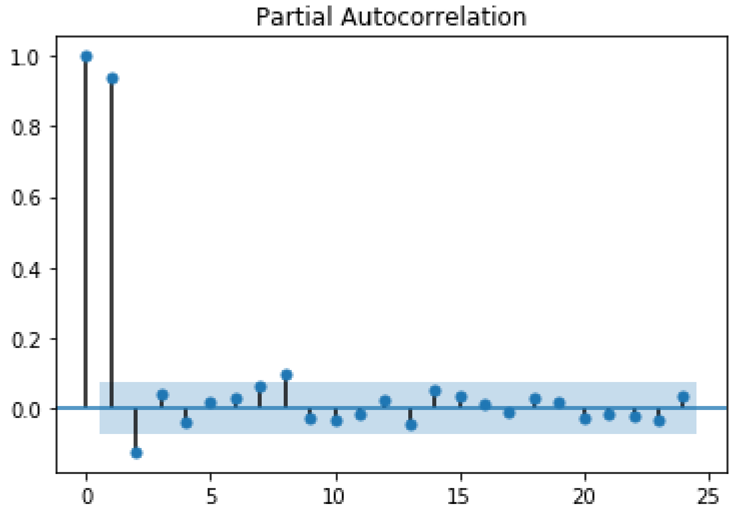
```
719
```

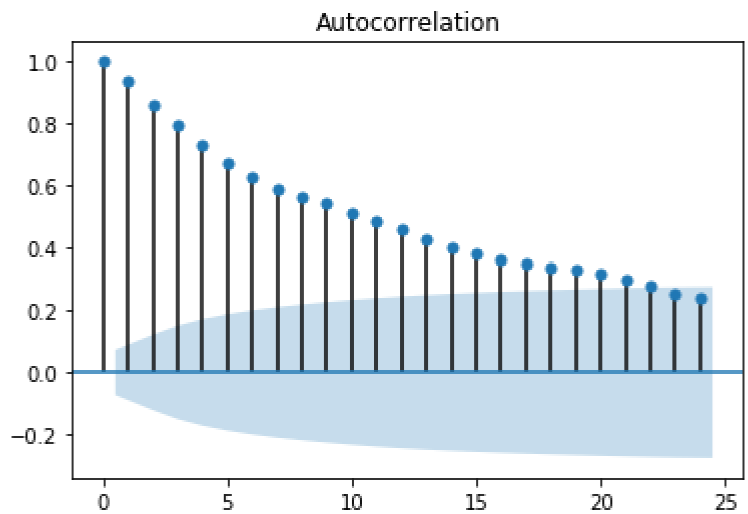
What does the autocorrelation function look like for our dataset?

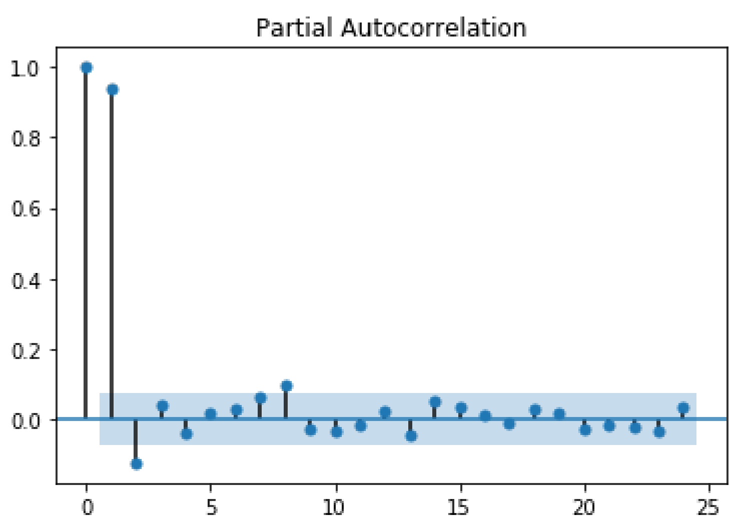
It looks like it is very positively correlated and that it is following something like a random walk. I am also going to do some test to make the data stationary so we can better see the trends.

In [28]:
```
from statsmodels.graphics.tsaplots import plot_acf
from statsmodels.graphics.tsaplots import plot_pacf

plot_acf(july, lags= 24, alpha=0.05)
plot_pacf(july, lags= 24, alpha=0.05)

#This is to determine the P and the Q
```

Out[28]:





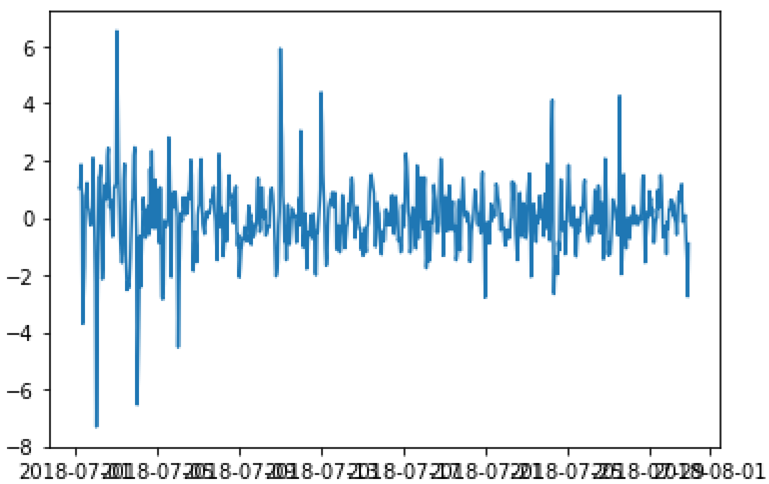


When I detrend the july time series, I can pass the window size and then use the .mean() method in order to make it stationary. Then we should be able to better see what the seasonal period is within the data.

In [29]:
```
july2 = july - july.rolling(4).mean()
```

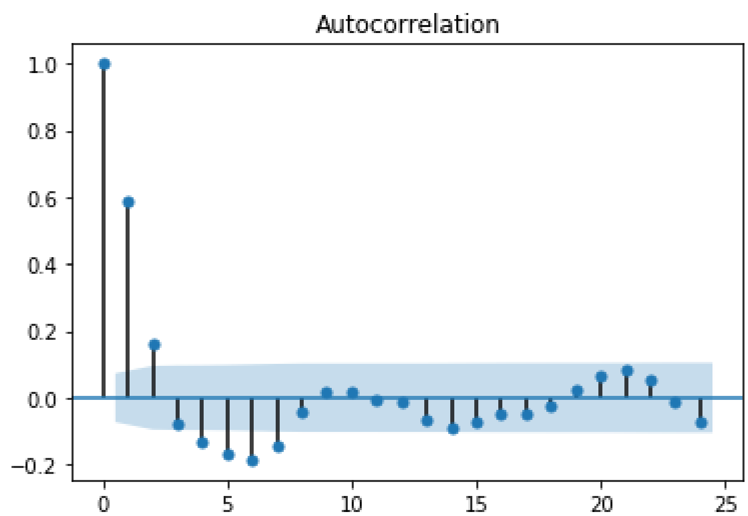
In [30]:
```
plt.plot(july2)
```

Out[30]: [<matplotlib.lines.Line2D at 0x2a960fde7c8>]



In [31]:
```
plot_acf(july2.dropna(), lags= 24, alpha=0.05)
```

Out[31]:



In [32]:
```
#!python -m pip install statsmodels
```

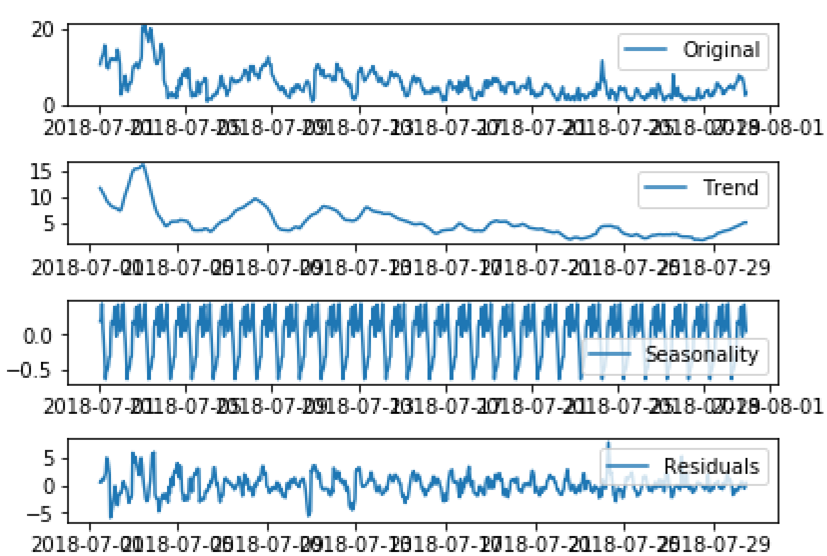
3. Modelling

3a. Decomposition

What does it mean to decompose time series data? It means breaking that data into 3 components:

Trend: The overall direction that the data is travelling in (like upwards or downwards) Seasonality: Cyclical patterns in the data Noise: The random variation in the data We can treat these components differently, depending on the question and what's appropriate in the context. They can either be added together in an additive model, or multiplied together in a multiplicative model.

In [33]:
```
# Import seasonal_decompose
from statsmodels.tsa.seasonal import seasonal_decompose

# Make a variable called decomposition, and assign it y passed to seasonal_decomp
decomposition = seasonal_decompose(july, period = 24)

#is this the right seasonality to use?

# Make three variables for trend, seasonal and residual components respectively.
# Assign them the relevant features of decomposition
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

# Plot the original data, the trend, the seasonality, and the residuals
plt.subplot(411)
plt.plot(july, label = 'Original')
plt.legend(loc = 'best')
plt.subplot(412)
plt.plot(trend, label = 'Trend')
plt.legend(loc = 'best')
plt.subplot(413)
plt.plot(seasonal, label = 'Seasonality')
plt.legend(loc = 'best')
plt.subplot(414)
plt.plot(residual, label = 'Residuals')
plt.legend(loc = 'best')
plt.tight_layout()
```



3b. Testing for stationarity with KPSS

As you know, when doing time series analysis we always have to check for stationarity. Imprecisely, a time series dataset is stationary just if its statistical features don't change over time. A little more precisely, a stationary time series dataset will have constant mean, variance, and covariance.

There are many ways to test for stationarity, but one of the most common is the KPSS test. The Null hypothesis of this test is that the time series data in question is stationary; hence, if the p-value is less than the significance level (typically 0.05, but we decide) then we reject the Null and infer that the data is not stationary.

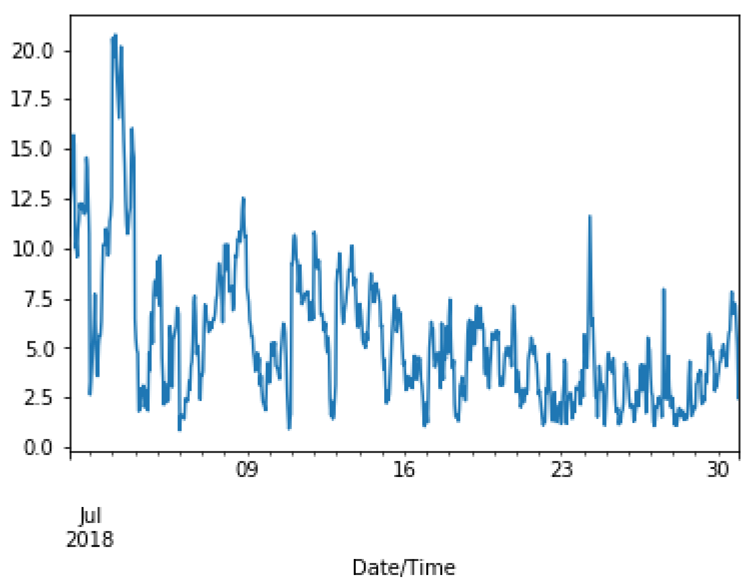
In [34]:
```
from statsmodels.tsa.stattools import kpss
kpss(july)
```

```
C:\Users\jeremy.wendt\Anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:
1661: FutureWarning: The behavior of using lags=None will change in the next re
lease. Currently lags=None is the same as lags='legacy', and so a sample-size l
ag length is used. After the next release, the default will change to be the sa
me as lags='auto' which uses an automatic lag length selection method. To silen
ce this warning, either use 'auto' or 'legacy'
  warn(msg, FutureWarning)
C:\Users\jeremy.wendt\Anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:
1685: InterpolationWarning: p-value is smaller than the indicated p-value
  warn("p-value is smaller than the indicated p-value", InterpolationWarning)
```

Out[34]:
```
(1.6659344221457195,
 0.01,
 20,
 {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})
```

In [35]:
```
july.plot()
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2a96119cbc8>
```



Create Stationary Dataset

We now have a constant variance, but we also need a constant mean.

We can do this by differencing our data. We difference a time series dataset when we create a new time series comprising the difference between the values of our existing dataset.

Python is powerful, and we can use the diff() function to do this. You'll notice there's one less value than our existing dataset (since we're taking the difference between the existing values).

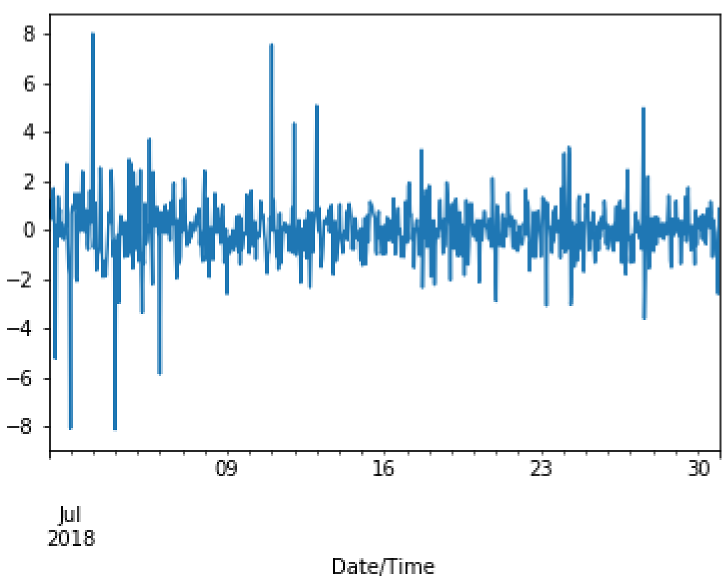
In [36]:
```
kpss(july.diff().dropna())
```

```
C:\Users\jeremy.wendt\Anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:
1661: FutureWarning: The behavior of using lags=None will change in the next re
lease. Currently lags=None is the same as lags='legacy', and so a sample-size l
ag length is used. After the next release, the default will change to be the sa
me as lags='auto' which uses an automatic lag length selection method. To silen
ce this warning, either use 'auto' or 'legacy'
  warn(msg, FutureWarning)
C:\Users\jeremy.wendt\Anaconda3\lib\site-packages\statsmodels\tsa\stattools.py:
1687: InterpolationWarning: p-value is greater than the indicated p-value
  warn("p-value is greater than the indicated p-value", InterpolationWarning)
```

Out[36]:
```
(0.020222651436651248,
 0.1,
 20,
 {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})
```

In [37]:
```
july.diff().plot()
```

Out[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2a96128ee48>
```



All of the p-values appear to indicate that all of these datasets would be a random walk.

In [38]:
```
results = adfuller(july)
print(results)
```

```
(-5.432492065126933, 2.8936597629465727e-06, 1, 717, {'1%': -3.439503230053971,
'5%': -2.8655794463678346, '10%': -2.5689210707289982}, 2204.938988120418)
```

Our p-value is now greater than 0.05, so we can accept the null hypothesis that our data is stationary after taking both the natural log and the difference.

3d. The ARIMA model

Recall that ARIMA models are based around the idea that it's possible to predict the next value in a time series by using information about the most recent data points. It also assumes there will be some randomness in our data that can't ever be predicted.

We can find some good parameters for our model using the sklearn and statsmodels libraries, and in particular mean_squared_error and ARIMA.

In [39]:
```
# Import mean_squared_error and ARIMA
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.arima_model import ARIMA
```

In [40]:
```
# Make a function called evaluate_arima_model to find the MSE of a single ARIMA m
def evaluate_arima_model(data, arima_order):
    # Needs to be an integer because it is later used as an index.
    # Use int()
    split=int(len(data) * 0.8)
    # Make train and test variables, with 'train, test'
    train, test= data[0:split], data[split:len(data)]
    past=[x for x in train]
    # make predictions
    predictions = list()
    for i in range(len(test)):#timestep-wise comparison between test data and one
        model = ARIMA(past, order=arima_order)
        model_fit = model.fit(disp=0)
        future = model_fit.forecast()[0]
        predictions.append(future)
        past.append(test[i])
    # calculate out of sample error
    error = mean_squared_error(test, predictions)
    # Return the error
    return error
```

In [41]:
```
# Make a function called evaluate_models to evaluate different ARIMA models with
def evaluate_models(dataset, p_values, d_values, q_values):
    best_score, best_cfg = float("inf"), None
    # Iterate through p_values
    for p in p_values:
        # Iterate through d_values
        for d in d_values:
            # Iterate through q_values
            for q in q_values:
                # p, d, q iterator variables in that order
                order = (p,d,q)
                try:
                    # Make a variable called mse for the Mean squared error
                    mse = evaluate_arima_model(dataset, order)
                    if mse < best_score:
                        best_score, best_cfg = mse, order
                    print(order,mse)
                    print('ARIMA%s MSE=%.3f' % (order,mse))
                except:
                    continue
    return print('Best ARIMA%s MSE=%.3f' % (best_cfg, best_score))
```

In [42]:
```
# Now, we choose a couple of values to try for each parameter: p_values, d_values
# Fill in the blanks as appropriate
p_values = [x for x in range(0, 3)]
d_values = [x for x in range(0, 3)]
q_values = [x for x in range(0, 3)]
```

In [43]:
```
july.diff()
```

Out[43]:
```
Date/Time
2018-07-01 01:00:00         NaN
2018-07-01 02:00:00    1.214581
2018-07-01 03:00:00    0.769775
2018-07-01 04:00:00    0.465558
2018-07-01 05:00:00    0.908240
                         ...
2018-07-30 19:00:00   -0.106714
2018-07-30 20:00:00   -0.983080
2018-07-30 21:00:00   -1.128496
2018-07-30 22:00:00   -2.590861
2018-07-30 23:00:00    0.879159
Freq: H, Name: Wind Speed (m/s), Length: 719, dtype: float64
```

In [44]:

```
# Finally, we can find the optimum ARIMA model for our data.
# Nb. this can take a while...!
import warnings
warnings.filterwarnings("ignore")
evaluate_models(july.diff().dropna(), p_values, d_values, q_values)
```

```
(0, 0, 0) 0.8938800987869896
ARIMA(0, 0, 0) MSE=0.894
(0, 0, 1) 0.9046955044212788
ARIMA(0, 0, 1) MSE=0.905
(0, 0, 2) 0.8840199998151496
ARIMA(0, 0, 2) MSE=0.884
(0, 1, 0) 1.7943013036350632
ARIMA(0, 1, 0) MSE=1.794
(0, 1, 1) 0.8977710603956537
ARIMA(0, 1, 1) MSE=0.898
(0, 1, 2) 0.9085597663270693
ARIMA(0, 1, 2) MSE=0.909
(0, 2, 0) 4.890824503811945
ARIMA(0, 2, 0) MSE=4.891
(0, 2, 1) 1.8005472703231808
ARIMA(0, 2, 1) MSE=1.801
(0, 2, 2) 0.9016079442706008
ARIMA(0, 2, 2) MSE=0.902
(1, 0, 0) 0.9057589109839596
ARIMA(1, 0, 0) MSE=0.906
(1, 0, 1) 0.8922506896987965
ARIMA(1, 0, 1) MSE=0.892
(1, 0, 2) 0.8517687438632232
ARIMA(1, 0, 2) MSE=0.852
(1, 1, 0) 1.5277156855372072
ARIMA(1, 1, 0) MSE=1.528
(1, 1, 1) 0.9098874794933999
ARIMA(1, 1, 1) MSE=0.910
(1, 1, 2) 0.8814715065304601
ARIMA(1, 1, 2) MSE=0.881
(1, 2, 0) 3.3313160469007146
ARIMA(1, 2, 0) MSE=3.331
(2, 0, 0) 0.8847602376073489
ARIMA(2, 0, 0) MSE=0.885
(2, 0, 1) 0.8948953082470992
ARIMA(2, 0, 1) MSE=0.895
(2, 0, 2) 0.8485282397359503
ARIMA(2, 0, 2) MSE=0.849
(2, 1, 0) 1.2943776697489067
ARIMA(2, 1, 0) MSE=1.294
(2, 1, 1) 0.8889965458722067
ARIMA(2, 1, 1) MSE=0.889
(2, 2, 0) 2.5201225011271853
ARIMA(2, 2, 0) MSE=2.520
Best ARIMA(2, 0, 2) MSE=0.849
```

In [45]:
```
p=2
d=0
q=2
model = ARIMA(july.diff().dropna(), order=(p,d,q))
model_fit = model.fit()
forecast = model_fit.forecast(24)
```

Now we have to convert the stationary dataset back to the orginal form in order to forecast properly on the dataset we want.

In [46]:
```
forecast[0]

x, x_diff = july.iloc[718], forecast[0]
forecast_aug = np.r_[x, x_diff].cumsum()
```

In [47]:
```
#Call summary() on model_fit
model_fit.summary()
```

Out[47]:

ARMA Model Results

Dep. Variable:	Wind Speed (m/s)	**No. Observations:**	718
Model:	ARMA(2, 2)	**Log Likelihood**	-1134.442
Method:	css-mle	**S.D. of innovations**	1.172
Date:	Fri, 04 Dec 2020	**AIC**	2280.884
Time:	12:20:41	**BIC**	2308.342
Sample:	07-01-2018	**HQIC**	2291.485
	- 07-30-2018		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0093	0.002	-4.352	0.000	-0.013	-0.005
ar.L1.Wind Speed (m/s)	0.6673	0.272	2.449	0.014	0.133	1.201
ar.L2.Wind Speed (m/s)	0.2025	0.252	0.805	0.421	-0.290	0.695
ma.L1.Wind Speed (m/s)	-0.6321	0.262	-2.409	0.016	-1.146	-0.118
ma.L2.Wind Speed (m/s)	-0.3679	0.262	-1.402	0.161	-0.882	0.146

Roots

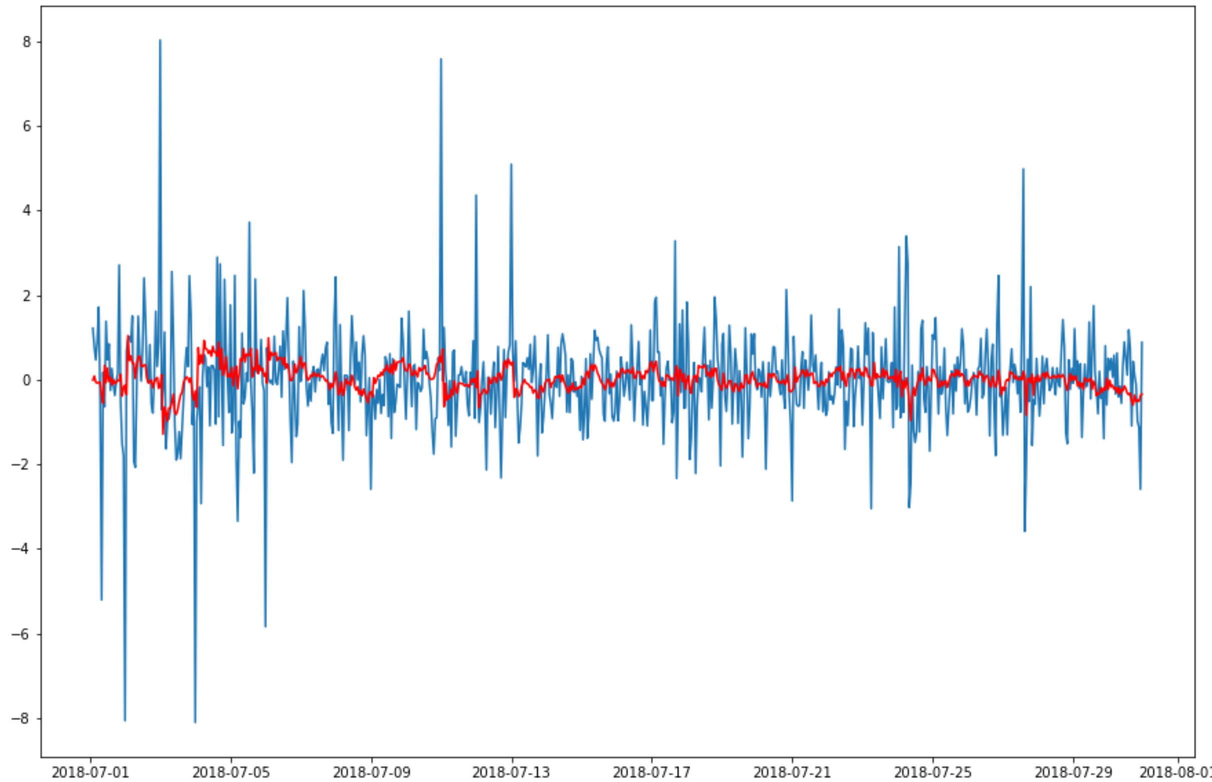
	Real	Imaginary	Modulus	Frequency
AR.1	1.1188	+0.0000j	1.1188	0.0000
AR.2	-4.4143	+0.0000j	4.4143	0.5000
MA.1	1.0000	+0.0000j	1.0000	0.0000
MA.2	-2.7181	+0.0000j	2.7181	0.5000

3e. Visualize the results

Visualize our stationary forecasted dataset against the original stationary dataset.

In [48]:
```
# Call figure() and plot() on the plt
plt.figure(figsize=(15,10))
plt.plot(july.diff())
plt.plot(model_fit.predict(), color = 'red')
```

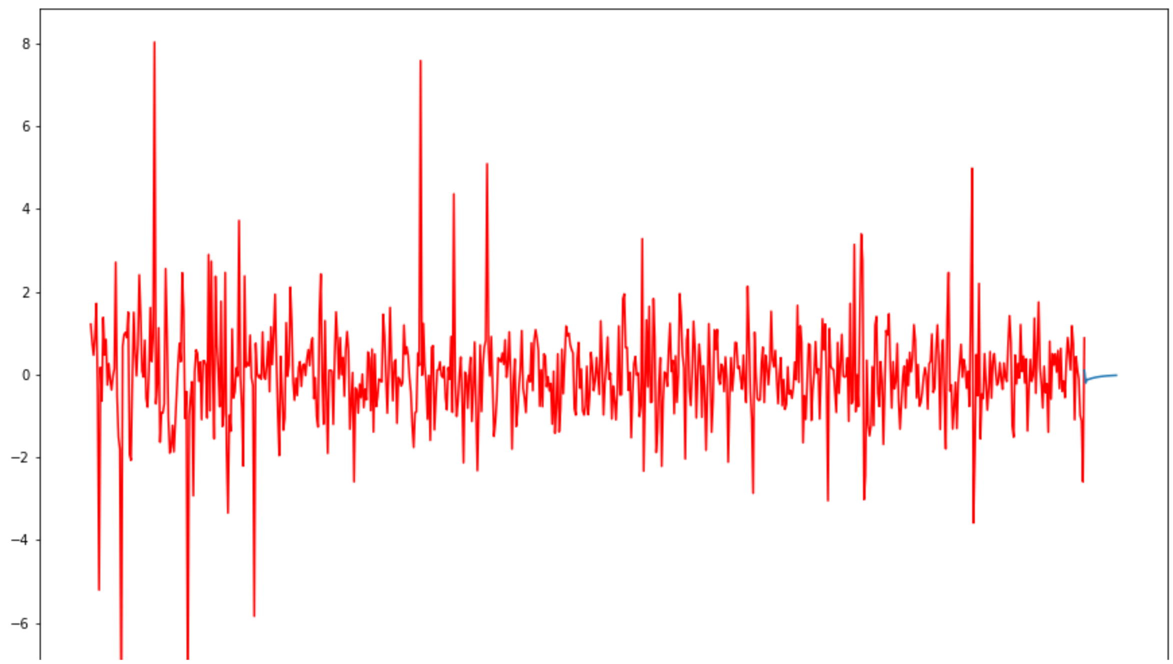
Out[48]:
```
[<matplotlib.lines.Line2D at 0x2a9665b7808>]
```



3f. Application: Forecasting

We've done well: our model fits pretty closely to our existing data. Let's now use it to forecast what's likely to occur in future.

In [49]:
```
# Declare a variable called forecast_period with the amount of 1 hour increments
# create a range of future dates that is the length of the periods you've chosen
forecast_period = 24
date_range = pd.date_range(july.index[-1], periods = forecast_period,
              freq='H').strftime("%Y-%m-%d, %h-%m-%s").tolist()

# Convert that range into a dataframe that includes your predictions
# First, call DataFrame on pd
future_months = pd.DataFrame(date_range, columns = ['Date/Time'])
# Let's now convert the 'Month' column to a datetime object with to_datetime
future_months['Date/Time'] = pd.to_datetime(future_months['Date/Time'])
future_months.set_index('Date/Time', inplace = True)
future_months['Prediction'] = forecast[0]

# Plot your future predictions
# Call figure() on plt
plt.figure(figsize=(15,10))
plt.plot(july.diff(), color = 'r')
plt.plot(future_months['Prediction'])
plt.show()
```

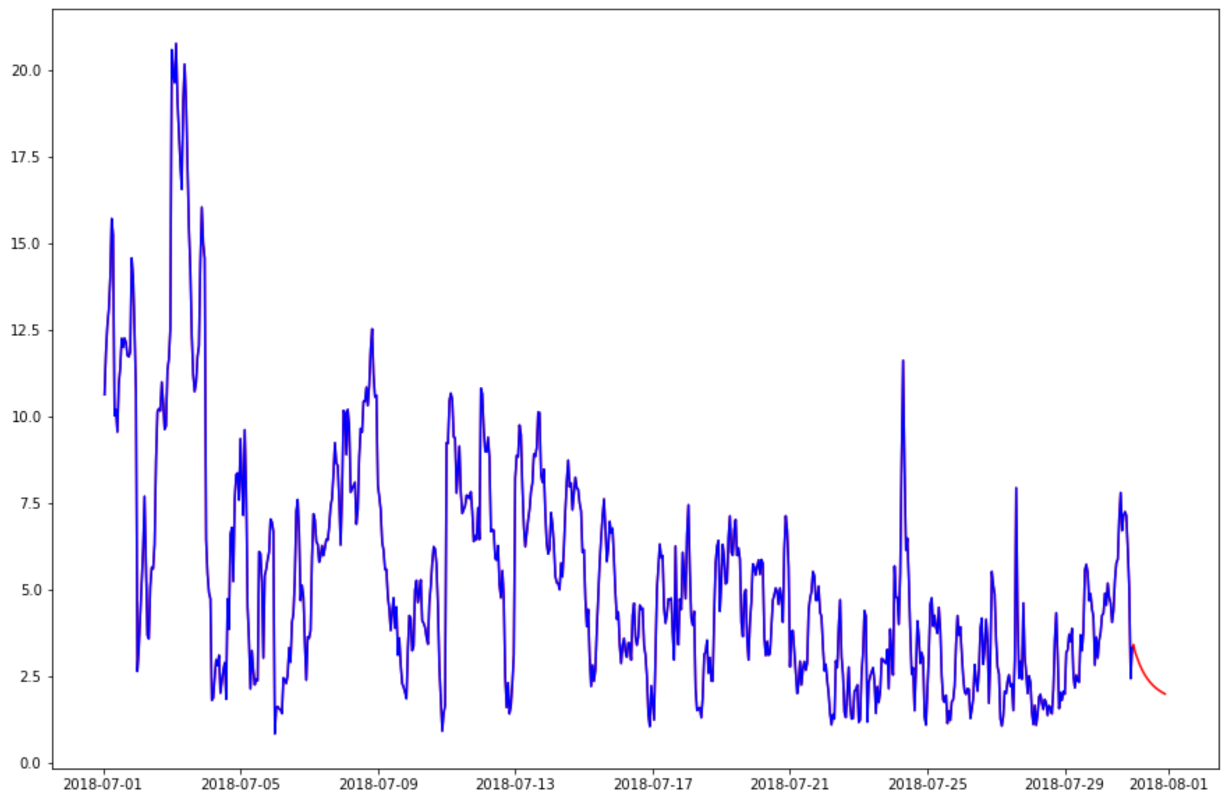


Results

The results here are not very encouraging. If we had used this ARIMA model to forecast our data from July 30th to August 9th using all of our July data as a baseline, we would not have created a very accurate forecast. This has been a good exercise in using all of the tools from our curriculum, but in practice, I would need to use a larger set of base data before creating a forecast I think. Also I would be curious how I can create a forecast that would imbed the seasonality of this data into it.

Lets explore what this data forecast would look like on our actual original data.

In [50]:
```
# Declare a variable called forecast_period with the amount of 1 hour increments
# create a range of future dates that is the length of the periods you've chosen
forecast_period = 24
date_range = pd.date_range(july.index[-1], periods = forecast_period,
              freq='H').strftime("%Y-%m-%d, %h-%m-%s").tolist()

# Convert that range into a dataframe that includes your predictions
# First, call DataFrame on pd
future_months = pd.DataFrame(date_range, columns = ['Date/Time'])
# Let's now convert the 'Month' column to a datetime object with to_datetime
future_months['Date/Time'] = pd.to_datetime(future_months['Date/Time'])
future_months.set_index('Date/Time', inplace = True)
future_months['Prediction'] = forecast_aug[:24]

# Plot your future predictions
# Call figure() on plt
plt.figure(figsize=(15,10))
plt.plot(july.append(future_months['Prediction']), color = 'r')
plt.plot(july, color = 'b')
plt.show()
```



4.1a Modeling with Prophet Package

[https://machinelearningmastery.com/time-series-forecasting-with-prophet-in-python/ (https://machinelearningmastery.com/time-series-forecasting-with-prophet-in-python/)](https://machinelearningmastery.com/time-series-forecasting-with-prophet-in-python/)

This is a different way to do time series forecasting. I want to look at it this way in order to verify my findings from the original ARIMA model.

In [52]:
```
from fbprophet import Prophet
```

```
Importing plotly failed. Interactive plots will not work.
```

In [53]:
```
july.columns = ['ds', 'y']
```

In [54]:
```
df = pd.DataFrame({'ds':july.index, 'y':july.values})

model1 = Prophet()

model1.fit(df)
```

```
INFO:fbprophet:Disabling yearly seasonality. Run prophet with yearly_seasonalit
y=True to override this.
```

Out[54]:
```
<fbprophet.forecaster.Prophet at 0x2a966539788>
```

In [55]:
```
df.tail()
```

Out[55]:

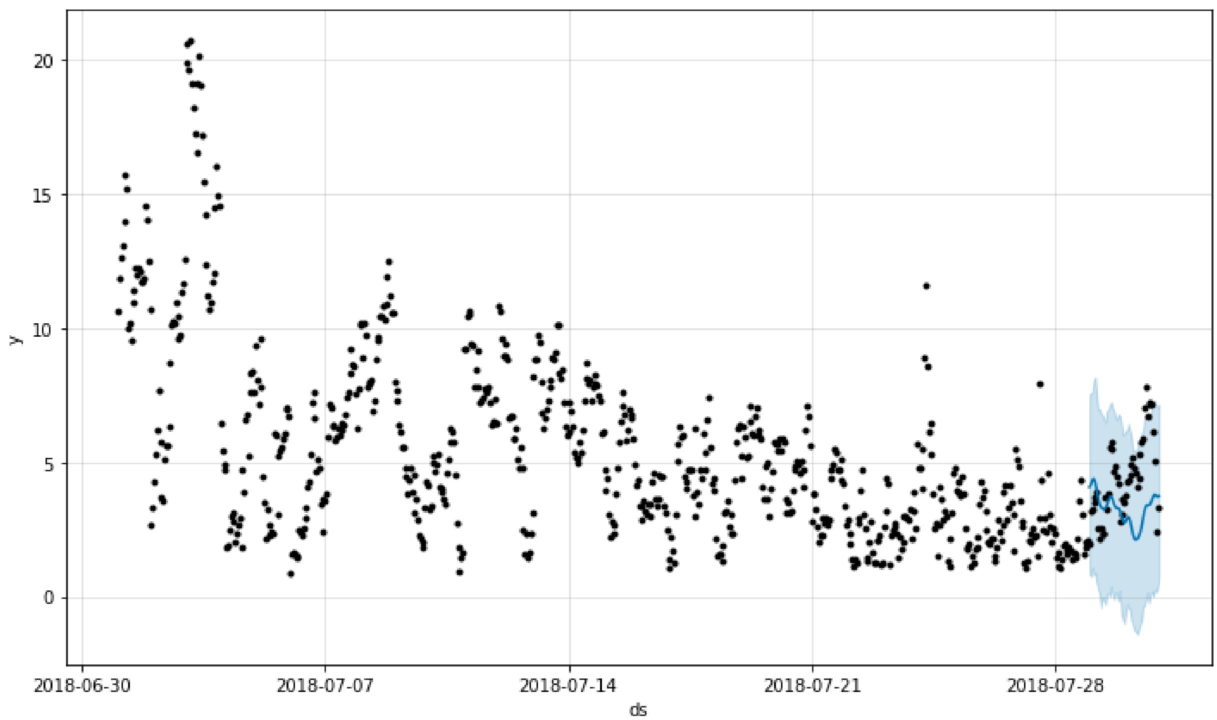
	ds	y
714	2018-07-30 19:00:00	7.141817
715	2018-07-30 20:00:00	6.158737
716	2018-07-30 21:00:00	5.030241
717	2018-07-30 22:00:00	2.439380
718	2018-07-30 23:00:00	3.318539

In [56]:
```
# define the period for which we want a prediction
from datetime import timedelta as td, datetime

start_date = '2018-07-29'
end_date = '2018-07-30'
d1 = datetime.strptime(start_date, '%Y-%m-%d')
d2 = datetime.strptime(end_date, '%Y-%m-%d')

def get_delta(d1, d2):
    delta = d2 - d1
    return delta

future = list()

delta = get_delta(d1,d2)
for i in range(delta.days * 48 + 1):
    future.append(d1 + td(hours=i))

future = pd.DataFrame(future)
future.columns = ['ds']
future['ds']= pd.to_datetime(future['ds'])
```

4b. Create In-Sample Forecast

In [57]:
```
forecast1 = model1.predict(future)
# summarize the forecast
print(forecast1[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail())
# plot forecast
model1.plot(forecast1)
plt.show()
```

```
                    ds      yhat  yhat_lower  yhat_upper
44 2018-07-30 20:00:00  3.717988    0.002020    7.222649
45 2018-07-30 21:00:00  3.797045    0.246296    7.309393
46 2018-07-30 22:00:00  3.770991    0.164304    7.120778
47 2018-07-30 23:00:00  3.713499    0.302595    7.049048
48 2018-07-31 00:00:00  3.741776    0.721046    7.156187
```

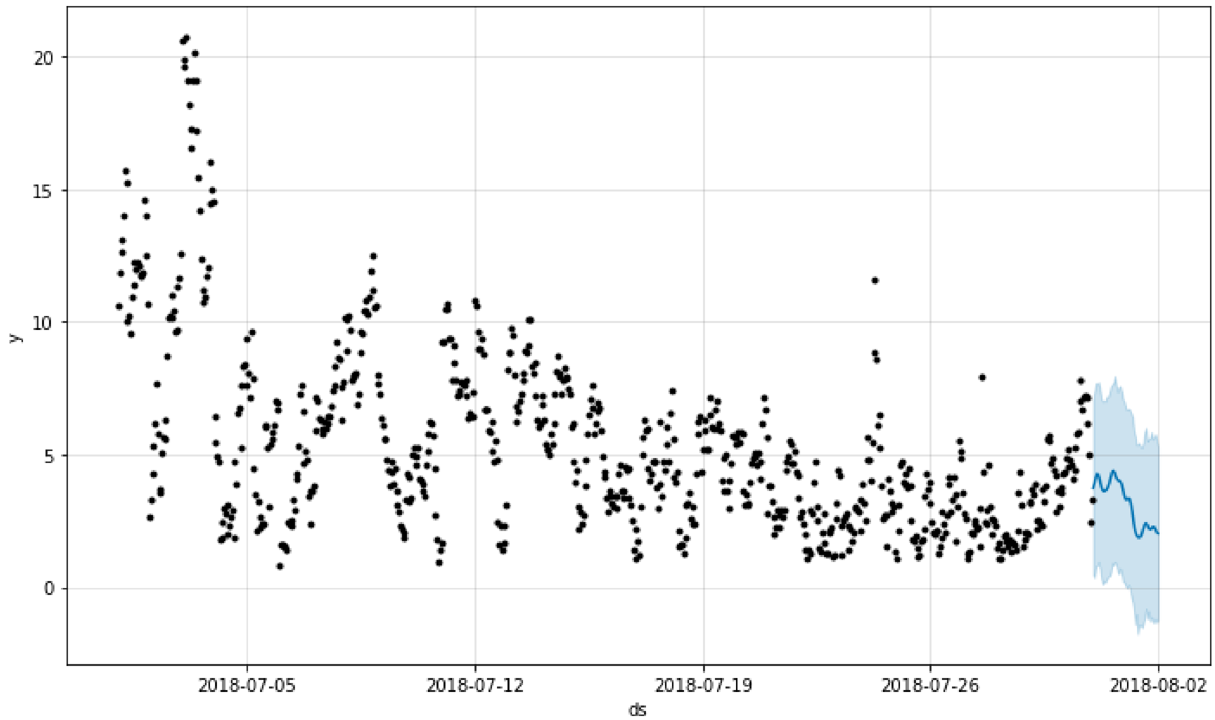


Create Out of Sample Forecast

In [58]:
```
# define the period for which we want a prediction
from datetime import timedelta as td, datetime

start_date = '2018-07-31'
end_date = '2018-08-01'
d1 = datetime.strptime(start_date, '%Y-%m-%d')
d2 = datetime.strptime(end_date, '%Y-%m-%d')

def get_delta(d1, d2):
    delta = d2 - d1
    return delta

future = list()

delta = get_delta(d1,d2)
for i in range(delta.days * 48 + 1):
    future.append(d1 + td(hours=i))

future = pd.DataFrame(future)
future.columns = ['ds']
future['ds']= pd.to_datetime(future['ds'])
```

In [59]:
```
forecast2 = model1.predict(future)
# summarize the forecast
print(forecast2[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].head())
# plot forecast
model1.plot(forecast2)
plt.show()
```

```
                   ds      yhat  yhat_lower  yhat_upper
0 2018-07-31 00:00:00  3.741776    0.468254    7.057435
1 2018-07-31 01:00:00  3.905116    0.369449    7.375861
2 2018-07-31 02:00:00  4.129400    0.798114    7.697811
3 2018-07-31 03:00:00  4.271355    0.828870    7.652195
4 2018-07-31 04:00:00  4.234579    0.965011    7.731457
```



4b. Manually Evaluate Forecast Model

In [60]:
```
# create test dataset, remove last 2 days
train = df.drop(df.index[-48:])
print(train.tail())
```

```
                     ds         y
666 2018-07-28 19:00:00  3.084877
667 2018-07-28 20:00:00  1.572593
668 2018-07-28 21:00:00  2.040446
669 2018-07-28 22:00:00  1.812334
670 2018-07-28 23:00:00  2.073747
```

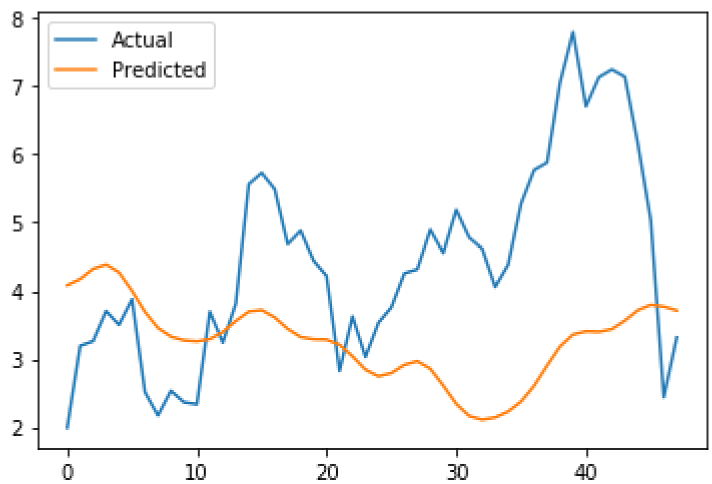
A forecast can then be made on the last 24 hours of date-times.

We can then retrieve the forecast values and the expected values from the original dataset and calculate a mean absolute error metric using the scikit-learn library.

In [61]:
```
from sklearn.metrics import mean_absolute_error

y_true = df['y'][-48:].values
y_pred = forecast1['yhat'][0:48].values
mae = mean_absolute_error(y_true, y_pred)
print('MAE: %.3f' % mae)
```

```
MAE: 1.688
```

In [62]:
```
# plot expected vs actual
plt.plot(y_true, label='Actual')
plt.plot(y_pred, label='Predicted')
plt.legend()
plt.show()
```



Findings

It seems like these models are consistently producing a similar result in predictions. Visually, Prophet Package seems more intuitive, but it is reassuring to see that both models came up with more or less the same prediction. This process shows that we can get a model with a MAE of 1.688 over the short term which isn't too bad. We could apply this to any time frame to consistently give us a measure to plan on.

Ideas for Further Research

Understanding how to do these forecasts on a more long term timeframe would be extremely beneficial. I think the next stages of research should go into that. Also, we could probably implement these models directly on the measure of power generation instead of wind speed since this is ultimately what drives the business model.

It would also be interesting to take this same concept and apply it to solar power since the fundamental of this business are so similar.

Recommendations on how to use findings

The client for this research could use this model for a number of solutions.

First of all, having a rough idea of what the wind patterns will be through the day should improve with our forecasting of power generation and should help us forecast potential revneue in the future.

Additionally, if we are able to build a model that can simulate wind power over a longer time frame, this can serve as a model for us to base our maintenance schedules off of.

Finally, these models should allow us to see the variability in wind speed over time or at least give us an estimate. This is very important because it allows us to better plan on how much backup generation we will need to ensure that the grid is operating with enough power to keep all of the users of power supplied consistently.