Predicting Energy Consumption Demand in Spain

```
A Python application predicting energy consumption in Spain, using differe
nt time-series analysis methods (Random Forest, SARIMA, TBATS, PROPHET) on
4 years of hourly data
```

We are going to take the following approach:

1. Problem Definition
2. Data
3. Evaluation
4. Features
5. Modelling
6. Experimentation

1. Problem definition

In a statement

> Given hourly consumption data, how well can we predict the demand consumption for the next year?

2. Data

> This data is from Kaggle. Link: https://www.kaggle.com/nicholasjhana/energy-consumption-generation-prices-and-weather (https://www.kaggle.com/nicholasjhana/energy-consumption-generation-prices-and-weather)

3. Evaluation

> Mean Absolute Error, Mean Square Error are the popular metrics for time series analysis..

4. Data Dictionarity

Create data dictionary

- Time: Datetime index localized to CET
- total load actual: actual electrical demand in MWh

In [83]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
import os

from sklearn.model_selection import TimeSeriesSplit,cross_val_score
from sklearn.linear_model import LinearRegression
from sklearn.neural_network import MLPRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor
from fbprophet import Prophet
from pmdarima import auto_arima
from tbats import TBATS, BATS


import statsmodels.api as sm
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

Data Exploration

Load the data into the dataframe

In [58]:

```
df = pd.read_csv('energy.csv')
df.head()
```

Out[58]:

	time	generation biomass	generation fossil brown coal/lignite	generation fossil coal-derived gas	generation fossil gas	generation fossil hard coal	generation fossil oil	ger f
0	2015-01-01 00:00:00+01:00	447.0	329.0	0.0	4844.0	4821.0	162.0	
1	2015-01-01 01:00:00+01:00	449.0	328.0	0.0	5196.0	4755.0	158.0	
2	2015-01-01 02:00:00+01:00	448.0	323.0	0.0	4857.0	4581.0	157.0	
3	2015-01-01 03:00:00+01:00	438.0	254.0	0.0	4314.0	4131.0	160.0	
4	2015-01-01 04:00:00+01:00	428.0	187.0	0.0	4130.0	3840.0	156.0	

5 rows × 29 columns

In [59]:

```
# Check dataframe shape
df.shape
```

Out[59]:

```
(35064, 29)
```

We just need to work with the total load actual column for time series analysis. So we will drop all unrelated columns

In [60]:

```
energy = df[['time','total load actual']]
```

In [61]:

```
# Remove the +01:00 from time
energy['time'] = energy['time'].map(lambda x: str(x)[:-6])
energy['time'][:5]
```

Out[61]:

```
0    2015-01-01 00:00:00
1    2015-01-01 01:00:00
2    2015-01-01 02:00:00
3    2015-01-01 03:00:00
4    2015-01-01 04:00:00
Name: time, dtype: object
```

In [62]:

```
# converting feature "time" to datatime format
energy['time'] = pd.to_datetime(energy['time'])
energy.dtypes
```

Out[62]:

```
time                     datetime64[ns]
total load actual               float64
dtype: object
```

Setting the index for the dataframe

In [63]:

```
# setting time as the index for the dataframe
energy = energy.set_index('time')
energy.head(3)
```

Out[63]:

	total load actual
time	
2015-01-01 00:00:00	25385.0
2015-01-01 01:00:00	24382.0
2015-01-01 02:00:00	22734.0

In [64]:

```
# verifying the indices of the dataframe
energy.index
```

Out[64]:

```
DatetimeIndex(['2015-01-01 00:00:00', '2015-01-01 01:00:00',
               '2015-01-01 02:00:00', '2015-01-01 03:00:00',
               '2015-01-01 04:00:00', '2015-01-01 05:00:00',
               '2015-01-01 06:00:00', '2015-01-01 07:00:00',
               '2015-01-01 08:00:00', '2015-01-01 09:00:00',
               ...
               '2018-12-31 14:00:00', '2018-12-31 15:00:00',
               '2018-12-31 16:00:00', '2018-12-31 17:00:00',
               '2018-12-31 18:00:00', '2018-12-31 19:00:00',
               '2018-12-31 20:00:00', '2018-12-31 21:00:00',
               '2018-12-31 22:00:00', '2018-12-31 23:00:00'],
              dtype='datetime64[ns]', name='time', length=35064, fre
q=None)
```

In [65]:

```
# Verifying for duplicate indexes in the dataframe
energy[energy.index.duplicated()]
```

Out[65]:

	total load actual
time	
2015-10-25 02:00:00	19775.0
2016-10-30 02:00:00	19786.0
2017-10-29 02:00:00	19867.0
2018-10-28 02:00:00	19965.0

In [66]:

```
# Removing duplicate indexes from the dataframe
energy = energy[~energy.index.duplicated()]
```

In [67]:

```
# Correcting the frequency (freq) of data collection from None to hourly (H)
energy = energy.asfreq('H')
energy.index
```

Out[67]:

```
DatetimeIndex(['2015-01-01 00:00:00', '2015-01-01 01:00:00',
               '2015-01-01 02:00:00', '2015-01-01 03:00:00',
               '2015-01-01 04:00:00', '2015-01-01 05:00:00',
               '2015-01-01 06:00:00', '2015-01-01 07:00:00',
               '2015-01-01 08:00:00', '2015-01-01 09:00:00',
               ...
               '2018-12-31 14:00:00', '2018-12-31 15:00:00',
               '2018-12-31 16:00:00', '2018-12-31 17:00:00',
               '2018-12-31 18:00:00', '2018-12-31 19:00:00',
               '2018-12-31 20:00:00', '2018-12-31 21:00:00',
               '2018-12-31 22:00:00', '2018-12-31 23:00:00'],
              dtype='datetime64[ns]', name='time', length=35064, fre
q='H')
```

In [68]:

```
energy.head()
```

Out[68]:

	total load actual
time	
2015-01-01 00:00:00	25385.0
2015-01-01 01:00:00	24382.0
2015-01-01 02:00:00	22734.0
2015-01-01 03:00:00	21286.0
2015-01-01 04:00:00	20264.0

In [69]:

```
energy.isnull().sum()
```

Out[69]:

```
total load actual    40
dtype: int64
```

Missing value imputations

In [70]:

```
# Forward fill the dataframe
energy.ffill(inplace = True)
energy.isnull().sum()
```

Out[70]:

```
total load actual    0
dtype: int64
```

Visualizing Trend in Data using Rolling Means

In [71]:

```
# We can visualize for year 2015 first, so that it's easier to see
year = 2015
s_load = energy[energy.index.year == year]
```

In [72]:

```
# Rolling means for daily data
df_load_24h = s_load.rolling(window = 24, center = True,min_periods=1).mean()
df_load_24h.head(3)
```

Out[72]:

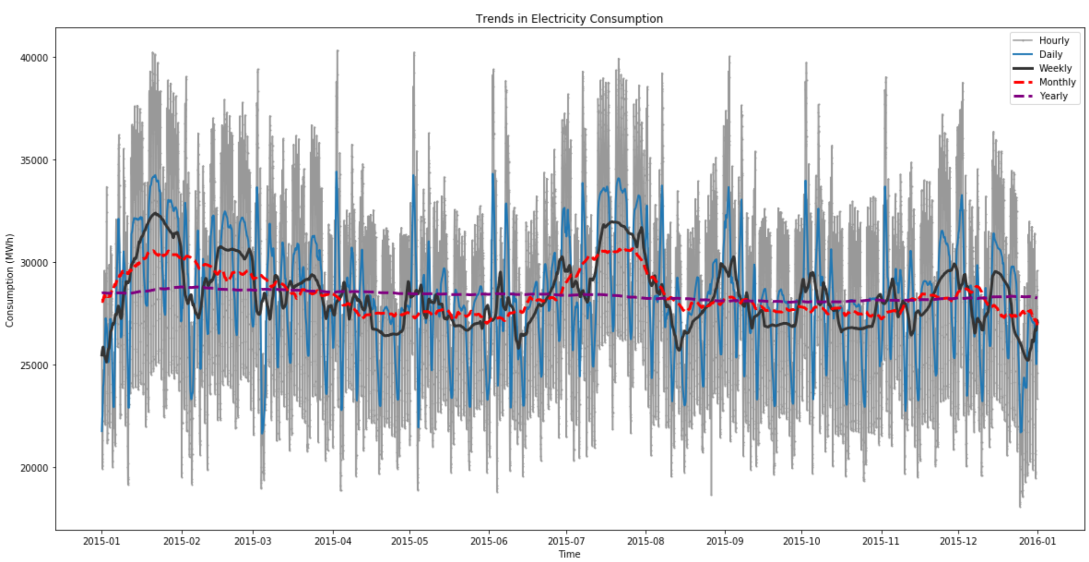
	total load actual
time	
2015-01-01 00:00:00	21739.250000
2015-01-01 01:00:00	21923.384615
2015-01-01 02:00:00	22122.642857

In [73]:

```
# Rolling means for weekly data
df_load_7d = s_load.rolling(window = 24*7, center = True, min_periods=1).mean()
# Rolling means for monthly data
df_load_30d = s_load.rolling(window = 24*30, center = True, min_periods=1).mean
()
# Rolling means for yearly data
df_load_365d = s_load.rolling(window = 24*365, center = True, min_periods=1).mea
n()
```

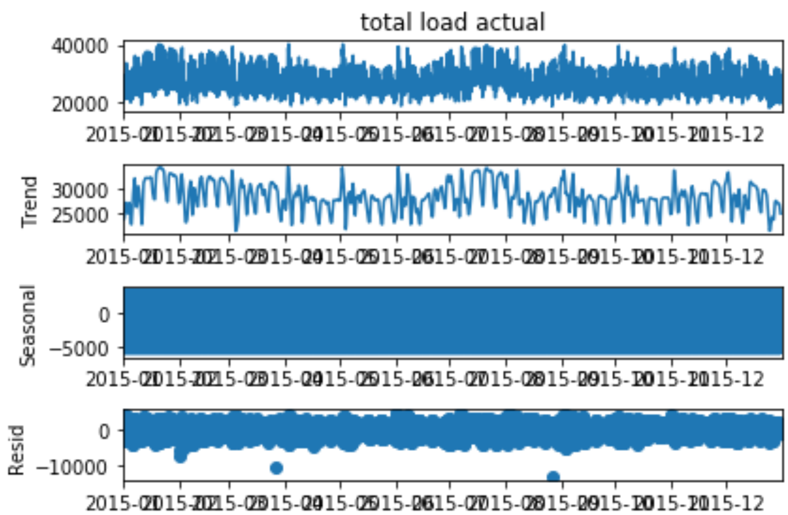
In [74]:

```
fig, ax = plt.subplots(figsize = (20,10))
# plotting hourly data
ax.plot(s_load, marker = '.', markersize = 2, color = '0.6', linestyle = None, l
abel = 'Hourly')
# plotting daily data
ax.plot(df_load_24h, linewidth = 2, linestyle = "-", label = 'Daily')
# plotting 7-day trend
ax.plot(df_load_7d, linewidth = 3, color = '0.2', label = 'Weekly')
# plotting 30-day trend
ax.plot(df_load_30d, linewidth = 3,color = 'red', linestyle = '--', label = 'Mon
thly' )
# plotting 365-day trend
ax.plot(df_load_365d, linewidth = 3,color = 'purple', linestyle = '--', label =
'Yearly' )


ax.xaxis.set_major_locator(mdates.MonthLocator())
ax.legend()
ax.set_xlabel('Time')
ax.set_ylabel('Consumption (MWh)')
ax.set_title('Trends in Electricity Consumption');
```



In [9]:

```
# Seasonality and Trend Check Test
from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(energy.loc[energy.index.year==2015], model='additiv
e');
result.plot();
```



Visualizing Yearly trend in energy consumption

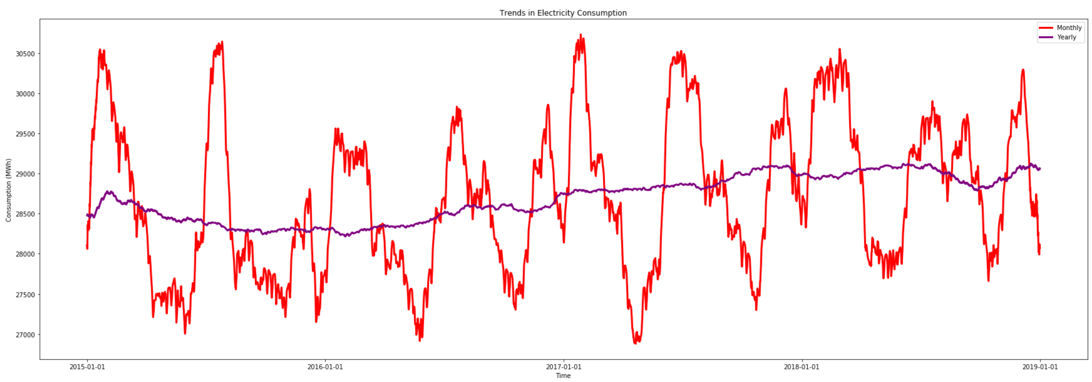
    The above graph is too difficult to see, we can see the data in more detai
    l

In [75]:

```
# Rolling means for monthly data for all years
df_load_30d = energy.rolling(window = 24*30, center = True, min_periods=1).mean
()
# Rolling means for yearly data
df_load_365d = energy.rolling(window = 24*365, center = True, min_periods=1).mea
n()
```

In [76]:

```
fig, ax = plt.subplots(figsize = (30,10))
# plotting 30-day trend
ax.plot(df_load_30d, linewidth = 3,color = 'red', linestyle = '-', label = 'Mont
hly' )
# plotting 365-day trend
ax.plot(df_load_365d, linewidth = 3,color = 'purple', linestyle = '-', label =
'Yearly' )
ax.xaxis.set_major_locator(mdates.YearLocator())
ax.legend()
ax.set_xlabel('Time')
ax.set_ylabel('Consumption (MWh)')
ax.set_title('Trends in Electricity Consumption');
```



Plot reveals data has a very slight upward trend and but it is not significant. But we see indication of yearly seasonality, with summer and winter months have higher consumption.

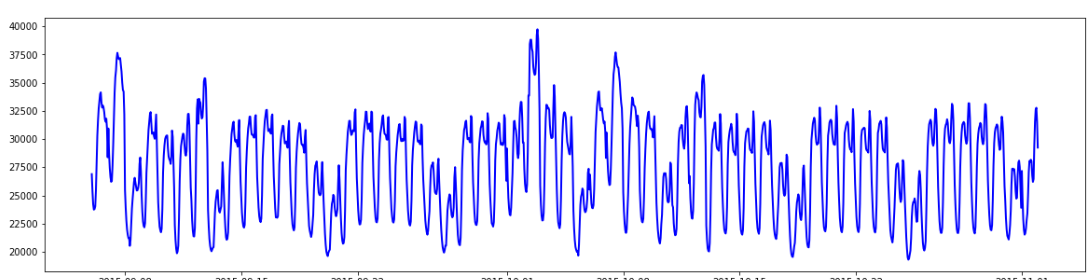
Visualizing to see if we have Weekly seasonality in energy consumption

In [77]:

```
# Zoom in on hourly data for a random week
fig, ax = plt.subplots(figsize = (20,5))
# plotting hourly data (Sunday-Saturday)
ax.plot(s_load['2015-09-06':'2015-11-01'], linestyle = '-',linewidth = 2, color
= 'blue', label = 'Weekly')
```

Out[77]:

```
[<matplotlib.lines.Line2D at 0x7fbfa3d2a240>]
```



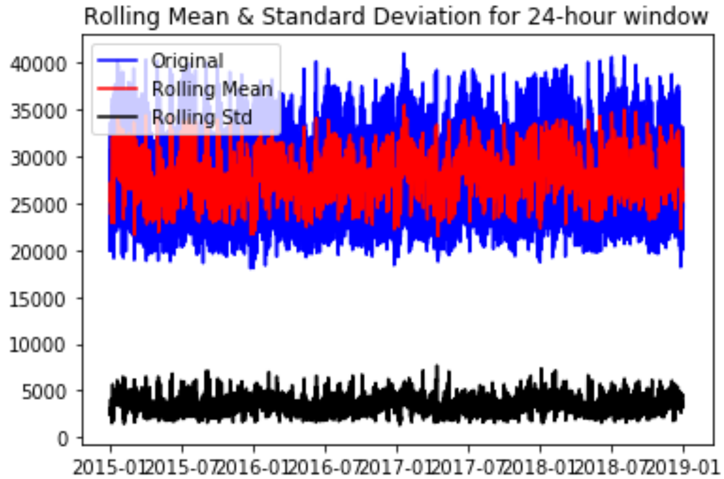
Plots shows weekly seasonality, with lowest consumption peaks on Saturdays and Sundays

Testing for Stationarity

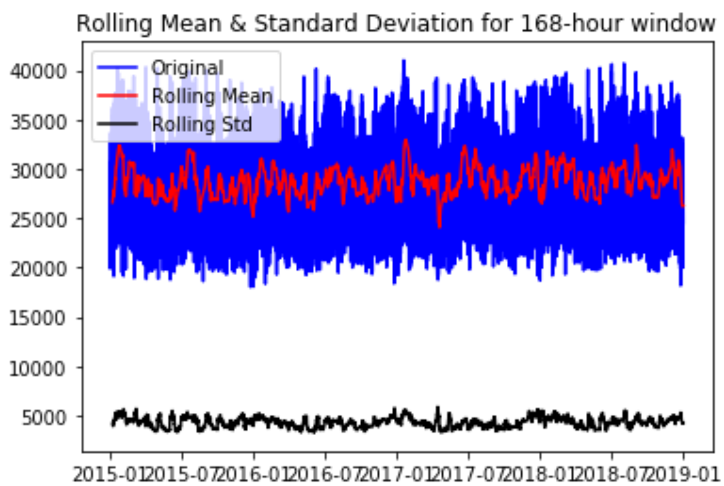
We will use Dickey Fuller test for Stationarity

In [78]:

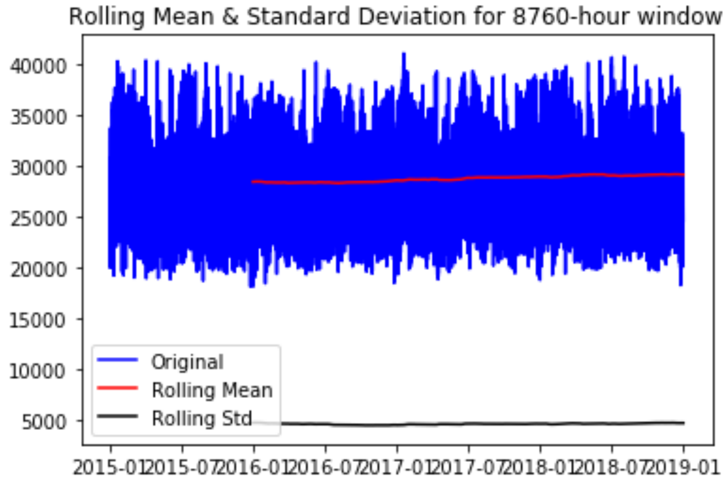
```
from statsmodels.tsa.stattools import adfuller
def test_stationarity(timeseries,win):

    #Determing rolling statistics
    rolmean = timeseries.rolling(window=win).mean()
    rolstd = timeseries.rolling(window=win).std()

    #Plot rolling statistics:
    orig = plt.plot(timeseries, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation for ' + str(win) + '-hour windo
w')
    plt.show(block=False)

    #Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags U
sed','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (round(dfoutput,3))

#runnning ADF test for different windows as seasonality is daily,weekly and year
ly
window=[24,24*7,24*365]
for i in window:
    test_stationarity(energy,i)
```




```
Results of Dickey-Fuller Test:
Test Statistic                   -21.473
p-value                            0.000
#Lags Used                        52.000
Number of Observations Used    35011.000
Critical Value (1%)               -3.431
Critical Value (5%)               -2.862
Critical Value (10%)              -2.567
dtype: float64
```




```
Results of Dickey-Fuller Test:
Test Statistic                   -21.473
p-value                            0.000
#Lags Used                        52.000
Number of Observations Used    35011.000
Critical Value (1%)               -3.431
Critical Value (5%)               -2.862
Critical Value (10%)              -2.567
dtype: float64
```



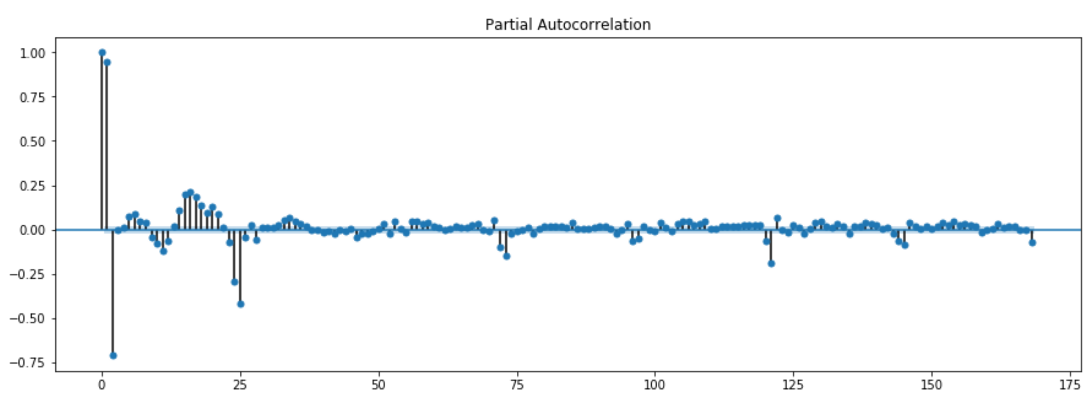

```
Results of Dickey-Fuller Test:
Test Statistic                  -21.473
p-value                           0.000
#Lags Used                       52.000
Number of Observations Used   35011.000
Critical Value (1%)              -3.431
Critical Value (5%)              -2.862
Critical Value (10%)             -2.567
dtype: float64
```

p-value is close to 0. Thus reject null hypothesis. The series is Stationary

Plotting partial autocorrelation

In [84]:

```
# importing statsmodel
from statsmodels.graphics.tsaplots import plot_pacf
# plotting the data partial autocorralation
fig, ax = plt.subplots(figsize = (15,5))
plot_pacf(energy['total load actual'].loc['2015-01':'2016-01'], ax = ax, lags=16
8, alpha = 0.05, method = 'ols');
```



From partial autocorrelation plot, we see that lag-1, lag -2, lag-3, lag-24 is highly autocorrelated

Modelling

Use 1st 3 years to train and last year to test. We will try out first with regression models, then time series models

1. Regression models: Linear Reg, KNN, Random Forest

In [79]:

```
energy.head()
```

Out[79]:

	total load actual
time	
2015-01-01 00:00:00	25385.0
2015-01-01 01:00:00	24382.0
2015-01-01 02:00:00	22734.0
2015-01-01 03:00:00	21286.0
2015-01-01 04:00:00	20264.0

In [80]:

```
# According to the above partial autocorrelation result, we will include lag 1,
 lag 2, lag 24, lag 168 in our model
energy_consumption = energy.copy()
energy_consumption.loc[:,'LastHourConsumption']=energy_consumption.shift()
energy_consumption.loc[:,'Last2hConsumption']=energy_consumption.shift(2)
energy_consumption.loc[:,'Last24hConsumption']=energy_consumption.shift(24)
energy_consumption.loc[:,'LastWeekConsumption']=energy.shift(24*7)
energy_consumption = energy_consumption.dropna()
energy_consumption.head()
```

Out[80]:

	total load actual	LastHourConsumption	Last2hConsumption	Last24hConsumption	LastWeek(
time					
2015-01-08 00:00:00	26788.0	30477.0	32697.0	30518.0	
2015-01-08 01:00:00	25146.0	26788.0	30477.0	28484.0	
2015-01-08 02:00:00	23889.0	25146.0	26788.0	27026.0	
2015-01-08 03:00:00	23046.0	23889.0	25146.0	26248.0	
2015-01-08 04:00:00	22587.0	23046.0	23889.0	25838.0	

Splitting Data

In [81]:

```
train_col=['LastHourConsumption',"Last2hConsumption","Last24hConsumption","LastW
eekConsumption"]
X_train = energy_consumption.loc['2015-01-10':'2017-12-31'][train_col]
y_train = energy_consumption.loc['2015-01-10':'2017-12-31']['total load actual']

X_test = energy_consumption.loc[energy_consumption.index.year>=2018][train_col]
y_test = energy_consumption.loc[energy_consumption.index.year>=2018]['total load
actual']
X_train.tail(3)
```

Out[81]:

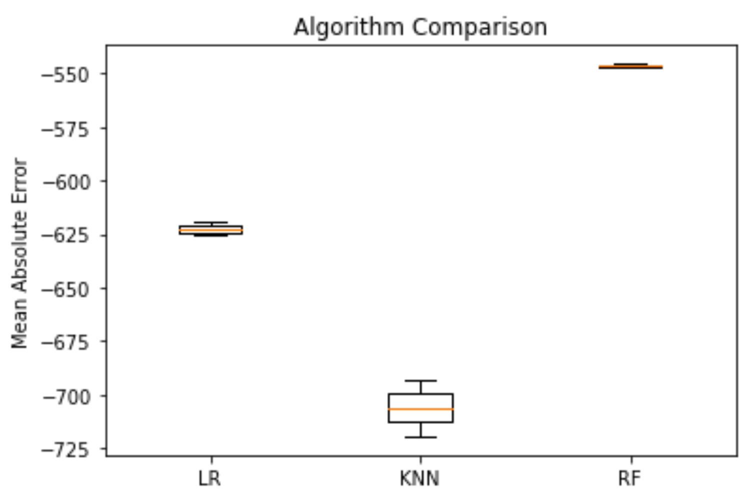
	LastHourConsumption	Last2hConsumption	Last24hConsumption	LastWeekConsumpt
time				
2017-12-31 21:00:00	28666.0	29097.0	29311.0	2761
2017-12-31 22:00:00	27260.0	28666.0	28286.0	2554
2017-12-31 23:00:00	25043.0	27260.0	26363.0	2459

Spot Check Algorithms

In [84]:

```
models=[('LR',LinearRegression()),
        ('KNN',KNeighborsRegressor()),
        ('RF',RandomForestRegressor(n_jobs = -1))]

names=[]
results=[]
for name,model in models:
    ts_crossval=TimeSeriesSplit(n_splits=2)
    cv_results = cross_val_score(model, X_train, y_train, cv=ts_crossval,
    scoring='neg_mean_absolute_error')
    print(ts_crossval)
    results.append(cv_results)
    names.append(name)
    print('%s: %f (%f)' % (name, cv_results.mean(), cv_results.std()))
# Compare Algorithms
plt.boxplot(results, labels=names)
plt.ylabel("Mean Absolute Error")
plt.title('Algorithm Comparison');
```

```
TimeSeriesSplit(max_train_size=None, n_splits=2)
LR: -622.358300 (3.381914)
TimeSeriesSplit(max_train_size=None, n_splits=2)
KNN: -706.217123 (13.229956)
TimeSeriesSplit(max_train_size=None, n_splits=2)
RF: -546.287509 (0.881970)
```



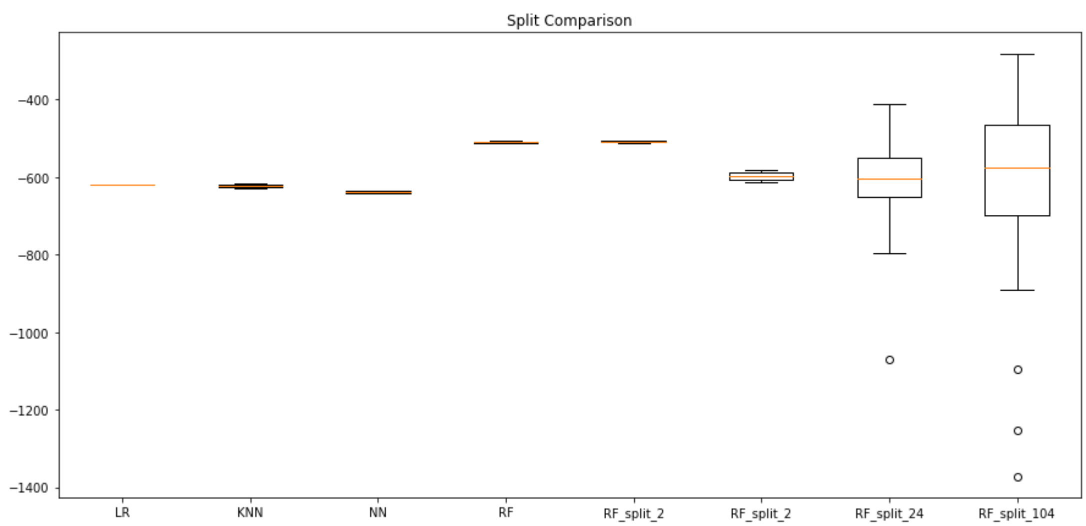
Seems like Random Forest gives us the best result

Find the best split for time series split

In [15]:

```
model=RandomForestRegressor()

split=[2,24,104]
for i in split:
    ts_crossval=TimeSeriesSplit(n_splits=i)
    cv_results = cross_val_score(model, X_train[X_train.index.year ==2015], y_tr
ain[y_train.index.year ==2015], cv=ts_crossval,
    scoring='neg_mean_absolute_error')
    print(ts_crossval)
    results.append(cv_results)
    names.append('RF_split_'+str(i))
    print('%s: %f (%f)' % ('RF_split_'+str(i), cv_results.mean(), cv_results.std
()))
# Compare Algorithms

plt.figure(figsize=(15,7))
boxplot=plt.boxplot(results, labels=names)
plt.title('Split Comparison');
```

```
TimeSeriesSplit(max_train_size=None, n_splits=2)
RF_split_2: -597.218585 (16.660867)
TimeSeriesSplit(max_train_size=None, n_splits=24)
RF_split_24: -609.803636 (126.799322)
TimeSeriesSplit(max_train_size=None, n_splits=104)
RF_split_104: -597.274447 (177.208183)
```



Split 2 is the best result. This makes sense as we have 3 years in training data

Hyperparameter Tuning

In [86]:

```
from sklearn.model_selection import RandomizedSearchCV
model = RandomForestRegressor(n_jobs = -1)
param_search = {
    'n_estimators': np.arange(10,100,10),
    'max_depth' : [i for i in range(5,15)],
    'min_samples_split': np.arange(2,20,2),
    'min_samples_leaf': np.arange(1,20,2),
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_samples': [10000]}

tscv = TimeSeriesSplit(n_splits=2)
tuned_model = RandomizedSearchCV(estimator=model,
                                 param_distributions=param_search,
                                 scoring = 'neg_mean_squared_error',
                                 cv=tscv,
                                 verbose = True,
                                 random_state = 42)
tuned_model.fit(X_train, y_train)
```

```
Fitting 2 folds for each of 10 candidates, totalling 20 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurr
ent workers.
[Parallel(n_jobs=1)]: Done  20 out of  20 | elapsed:    6.8s finishe
d
```

Out[86]:

```
RandomizedSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=
2),
                   estimator=RandomForestRegressor(n_jobs=-1),
                   param_distributions={'max_depth': [5, 6, 7, 8, 9,
10, 11, 12,
                                                      13, 14],
                                        'max_features': ['auto', 'sq
rt',
                                                         'log2'],
                                        'max_samples': [10000],
                                        'min_samples_leaf': array([
1,  3,  5,  7,  9, 11, 13, 15, 17, 19]),
                                        'min_samples_split': array([
2,  4,  6,  8, 10, 12, 14, 16, 18]),
                                        'n_estimators': array([10, 2
0, 30, 40, 50, 60, 70, 80, 90])},
                   random_state=42, scoring='neg_mean_squared_erro
r',
                   verbose=True)
```

In [88]:

```
tuned_model.best_estimator_
```

Out[88]:

```
RandomForestRegressor(max_depth=14, max_features='log2', max_samples
=10000,
                      min_samples_leaf=5, n_estimators=30, n_jobs=-
1)
```

In [89]:

```
# Create function to evaluate model on a few different level
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

def show_scores(model):
    train_preds = model.predict(X_train)
    test_preds = model.predict(X_test)
    scores = {'Training MAE':mean_absolute_error(y_train, train_preds),
              'Test MAE':mean_absolute_error(y_test, test_preds),
              'Training MSE': mean_squared_error(y_train, train_preds),
              'Test MSE': mean_squared_error(y_test, test_preds),
             'Training R2': r2_score(y_train, train_preds),
             'Test R2': r2_score(y_test, test_preds)}
    return scores
```

In [90]:

```
show_scores(tuned_model)
```

Out[90]:

```
{'Training MAE': 482.3043168134137,
 'Test MAE': 563.7399686475769,
 'Training MSE': 505537.2521968224,
 'Test MSE': 670610.4423509492,
 'Training R2': 0.9756048672200919,
 'Test R2': 0.9686646585664426}
```

In [91]:

```
# Plug in the best parameters
ideal_rf = RandomForestRegressor(max_depth=14, max_features='log2', max_samples=
10000,
                      min_samples_leaf=5, n_estimators=30, n_jobs=-1)
ideal_rf.fit(X_train,y_train)
ideal_rf.feature_importances_
```

Out[91]:

```
array([0.53285623, 0.30136618, 0.07478104, 0.09099655])
```

In [92]:

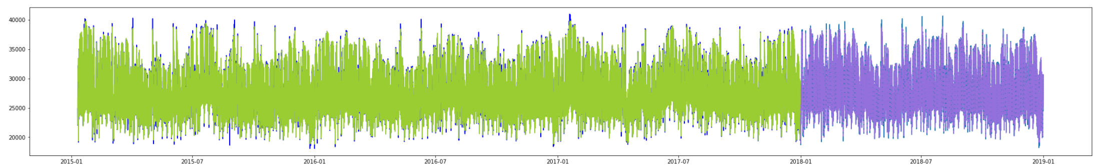
```
X_train.columns
```

Out[92]:

```
Index(['LastHourConsumption', 'Last2hConsumption', 'Last24hConsumpti
on',
       'LastWeekConsumption'],
      dtype='object')
```

In [94]:

```
# Plot the regression's result please
train_preds = ideal_rf.predict(X_train)
test_preds = ideal_rf.predict(X_test)

# Predicted load on training data
train_preds = pd.Series(data = train_preds, index = X_train.index)
# Predicted load on test data
test_preds = pd.Series(data = test_preds, index = X_test.index)
# Plot data
fig, ax = plt.subplots(figsize = (35,5))

ax.plot(y_train, color = 'blue')
ax.plot(y_test)

ax.plot(train_preds, color = 'YellowGreen')
ax.plot(test_preds, linestyle = '--', color = 'MediumPurple');
```



We have best metric result with Random Forest in all models

2. PROPHET

In [2]:

```
df=energy.copy()
df['date'] = df.index
df['hour'] = df['date'].dt.hour
df['dayofweek'] = df['date'].dt.dayofweek
df['quarter'] = df['date'].dt.quarter
df['month'] = df['date'].dt.month
df['year'] = df['date'].dt.year
df['dayofyear'] = df['date'].dt.dayofyear
df['dayofmonth'] = df['date'].dt.day
df['weekofyear'] = df['date'].dt.weekofyear

X = df[['hour','dayofweek','quarter','month','year',
       'dayofyear','dayofmonth','weekofyear']]
y=df['total load actual']
#X, y = create_features(energy['total load actual'], label='total load actual')

features_and_target = pd.concat([X, y], axis=1)
```

In [3]:

```
features_and_target.head()
```

Out[3]:

time	hour	dayofweek	quarter	month	year	dayofyear	dayofmonth	weekofyear	tot loa actu
2015-01-01 00:00:00	0	3	1	1	2015	1	1	1	25385.
2015-01-01 01:00:00	1	3	1	1	2015	1	1	1	24382.
2015-01-01 02:00:00	2	3	1	1	2015	1	1	1	22734.
2015-01-01 03:00:00	3	3	1	1	2015	1	1	1	21286.
2015-01-01 04:00:00	4	3	1	1	2015	1	1	1	20264.

In [4]:

```
features_and_target.tail()
```

Out[4]:

time	hour	dayofweek	quarter	month	year	dayofyear	dayofmonth	weekofyear	tot loa actu
2018-12-31 19:00:00	19	0	4	12	2018	365	31	1	30653.
2018-12-31 20:00:00	20	0	4	12	2018	365	31	1	29735.
2018-12-31 21:00:00	21	0	4	12	2018	365	31	1	28071.
2018-12-31 22:00:00	22	0	4	12	2018	365	31	1	25801.
2018-12-31 23:00:00	23	0	4	12	2018	365	31	1	24455.

Visualize

In [5]:

```
split_date = '01-Jan-2018'
energy_train = features_and_target.drop(['hour', 'dayofweek', 'quarter', 'month'
, 'year', 'dayofyear', 'dayofmonth',
                                         'weekofyear'],axis=1).loc[energy.index
<= split_date].copy()
energy_test = features_and_target.drop(['hour', 'dayofweek', 'quarter', 'month',
'year', 'dayofyear', 'dayofmonth',
                                         'weekofyear'],axis=1).loc[energy.index
> split_date].copy()
```

In [6]:

```
#prophet needs dataset with specific column names 'ds' and 'y'

energy_train.reset_index(inplace=True)
energy_train.rename(columns={'time':'ds','total load actual':'y'},inplace=True)
```

In [7]:

```
energy_train.head()
```

Out[7]:

	ds	y
0	2015-01-01 00:00:00	25385.0
1	2015-01-01 01:00:00	24382.0
2	2015-01-01 02:00:00	22734.0
3	2015-01-01 03:00:00	21286.0
4	2015-01-01 04:00:00	20264.0

In [ ]:

```
model=Prophet()
model.fit(energy_train)
```

In [38]:

```
energy_forecast=model.predict(df=energy_train)
```

In [55]:

```
energy_forecast.head(3)
```

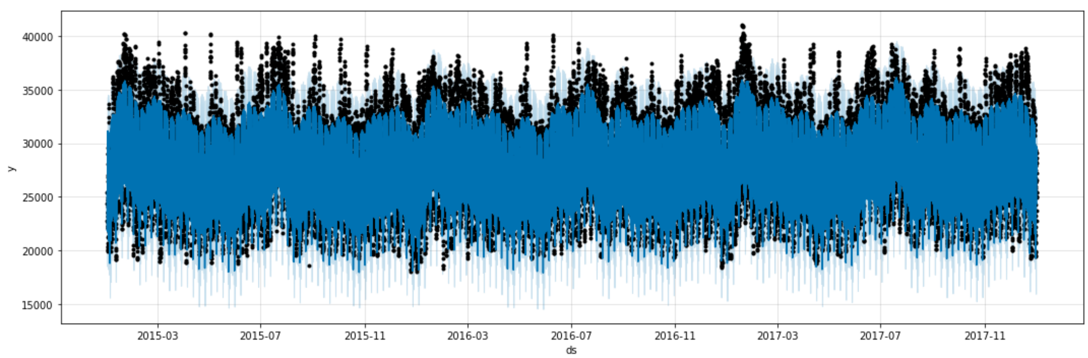
Out[55]:

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_t
0	2015-01-01 00:00:00	28351.943578	22306.596812	29034.274706	28351.943578	28351.943578	-2858.26
1	2015-01-01 01:00:00	28351.964238	20638.491524	27129.867464	28351.964238	28351.964238	-4516.78
2	2015-01-01 02:00:00	28351.984898	19276.698726	26022.634743	28351.984898	28351.984898	-5670.62

3 rows × 22 columns

In [56]:

```
# Plot the forecast for training data
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
fig = model.plot(energy_forecast,
                 ax=ax)
plt.show()
```



In [39]:

```
energy_test.reset_index(inplace=True)
energy_test.rename(columns={'time':'ds','total load actual':'y'},inplace=True)
energy_test_forecast=model.predict(energy_test)
```

In [58]:

```
fig = model.plot_components(energy_test_forecast)
```

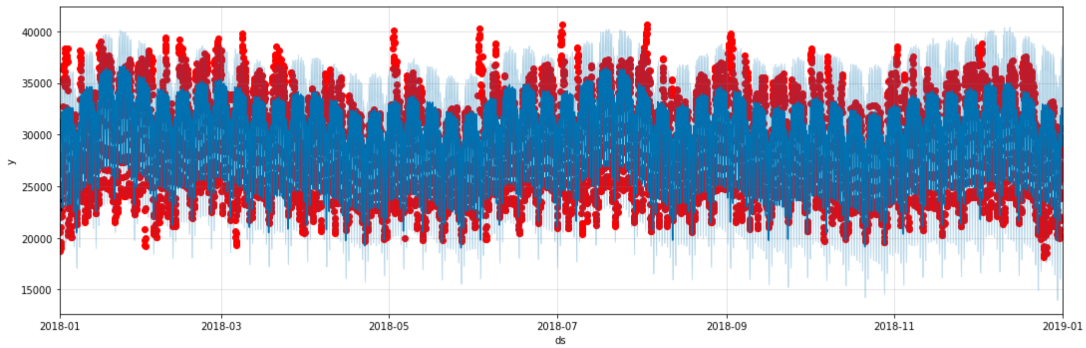
Forecast for 1st year

In [234]:

```
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
ax.scatter(energy_test['ds'], energy_test['y'], color='r')
fig = model.plot(energy_test_forecast, ax=ax)
ax.set_xlim(['2018-01','2019-01'])
```

Out[234]:

```
(736695.0, 737060.0)
```



Forecast for 1st month

In [ ]:

```
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
ax.plot(energy_test['ds'], energy_test['y'], color='r')
fig = model.plot(energy_test_forecast, ax=ax)
ax.set_xlim(['2018-01','2018-02'])
#red dots are actual data, blue line is the forecast, light blue shade is the co
nfidence interval for the forecast
```

In [40]:

```
energy_test_forecast.set_index('ds',inplace=True)
```

In [41]:

```
energy_test_grouped=pd.merge(energy_test,energy_test_forecast[['yhat','yhat_lowe
r','yhat_upper']],
                             left_on='ds',
                             right_on='ds',
                             how='inner')
```

In [42]:

```
energy_test_grouped.head()
```

Out[42]:

	ds	y	yhat	yhat_lower	yhat_upper
0	2018-01-01 01:00:00	22009.0	22831.441617	19335.729573	26171.425774
1	2018-01-01 02:00:00	20589.0	21821.401122	18378.800183	25116.348532
2	2018-01-01 03:00:00	19547.0	21270.306193	17980.058668	24519.627264
3	2018-01-01 04:00:00	18871.0	21244.331424	17612.886508	24670.224560
4	2018-01-01 05:00:00	18688.0	21946.526936	18530.624227	25439.250505

In [43]:

```
energy_forecast.set_index('ds',inplace=True)
energy_train_grouped=pd.merge(energy_train,energy_forecast[['yhat','yhat_lower',
'yhat_upper']],
                             left_on='ds',
                             right_on='ds',
                             how='inner')
energy_train_grouped.head()
```

Out[43]:

	ds	y	yhat	yhat_lower	yhat_upper
0	2015-01-01 00:00:00	25385.0	25493.680025	22537.473384	28840.216684
1	2015-01-01 01:00:00	24382.0	23835.181259	20455.244904	26984.187189
2	2015-01-01 02:00:00	22734.0	22681.355459	19487.492426	25896.608252
3	2015-01-01 03:00:00	21286.0	21985.854010	18614.653549	25306.224780
4	2015-01-01 04:00:00	20264.0	21815.804791	18312.177636	25303.209692

In [66]:

```
#metrics
from sklearn.metrics import mean_squared_error,r2_score
print('Mean Squared Error : %.2f'%mean_squared_error(y_true=energy_train_grouped
['y'],
                   y_pred=energy_train_grouped['yhat']))
print('R2_score :%.2f'%r2_score(energy_train_grouped['y'],energy_train_grouped
['yhat']))
```

```
Mean Squared Error : 6912833.19
R2_score :0.67
```

Among all models, I like Prophet as it gives out upper and lower bound of prediction. This is very useful in business decision making process

Daily Data For Models: TBATS, SARIMA

Because our dataset is too big and my computer cannot run all of it with Tbats and Sarima. We will work with daily data here

In [9]:

```
# Sum of data
daily_load = energy['total load actual'].resample('D').sum()
daily_load.head()
```

Out[9]:

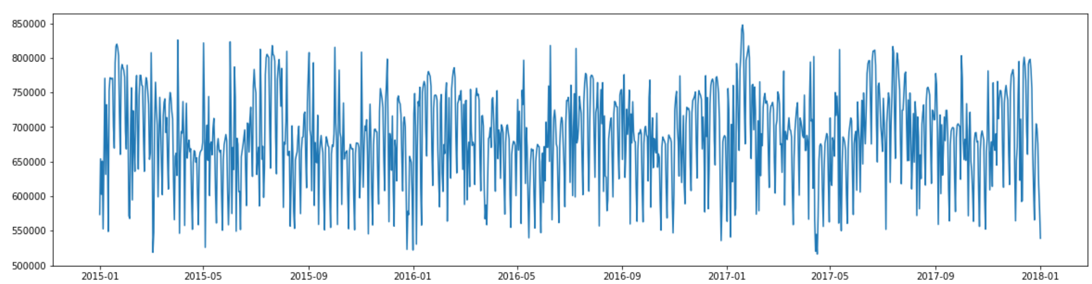
```
time
2015-01-01    573522.0
2015-01-02    654031.0
2015-01-03    602656.0
2015-01-04    650703.0
2015-01-05    552644.0
Freq: D, Name: total load actual, dtype: float64
```

In [10]:

```
# Splitting data
split_date = "2018-01-01"
daily_train = daily_load[:split_date]
daily_test = daily_load[split_date:]
plt.subplots(figsize = (20,5))
plt.plot(daily_train)
```

Out[10]:

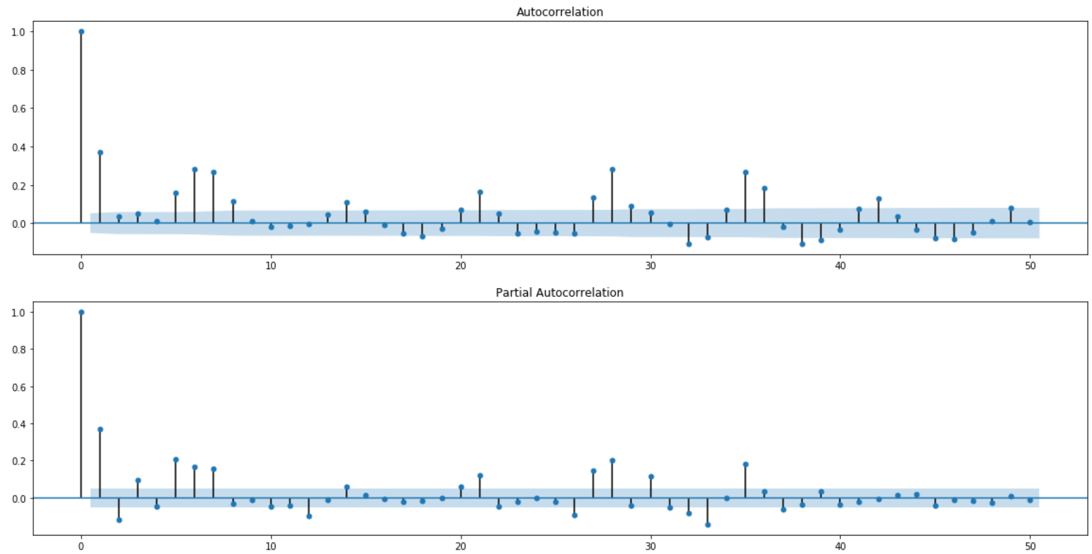
```
[<matplotlib.lines.Line2D at 0x7fb3ff023f98>]
```



SARIMA

In [11]:

```
# Run ACF and PACF for daily data
fig,ax = plt.subplots(2,1,figsize=(20,10))
fig = sm.graphics.tsa.plot_acf(daily_load, lags=50, ax=ax[0])
fig = sm.graphics.tsa.plot_pacf(daily_load, lags=50, ax=ax[1])
plt.show()
```



In [5]:

```
# Choose the best lags (p,q)
resDiff = sm.tsa.arma_order_select_ic(daily_train, max_ar=8, max_ma=8, ic='aic')
print('ARMA(p,q) =',resDiff['aic_min_order'],'is the best.')
```

```
ARMA(p,q) = (5, 4) is the best.
```

Our dataset has multi-seasonalities, and regular SARIMA function only allows us to input 1 seasonality. The trick here is to include the yearly seaosnality in exogenous data. We have 2016 as a leap year so we will divide the day with 365.25 instead of 365.

In [12]:

```
# prepare Fourier terms
exog = pd.DataFrame({'date': daily_load.index})
exog = exog.set_index(pd.PeriodIndex(exog['date'], freq='D'))
exog['sin30'] = np.sin(2 * np.pi * exog.index.dayofyear / 365.25)
exog['cos30'] = np.cos(2 * np.pi * exog.index.dayofyear / 365.25)
exog['sin30_2'] = np.sin(4 * np.pi * exog.index.dayofyear / 365.25)
exog['cos30_2'] = np.cos(4 * np.pi * exog.index.dayofyear / 365.25)
exog = exog.drop(columns=['date'])
exog_to_train = exog.loc[:split_date]
exog_to_test = exog.loc[split_date:]
print(exog_to_train.shape)
exog_to_train.head()
```

```
(1097, 4)
```

Out[12]:

	sin30	cos30	sin30_2	cos30_2
date				
2015-01-01	0.017202	0.999852	0.034398	0.999408
2015-01-02	0.034398	0.999408	0.068755	0.997634
2015-01-03	0.051584	0.998669	0.103031	0.994678
2015-01-04	0.068755	0.997634	0.137185	0.990545
2015-01-05	0.085906	0.996303	0.171177	0.985240

In [13]:

```
# Fit model
arima_model = auto_arima(daily_train, exogenous=exog_to_train,
                         start_p=5, start_q=4,
                         max_p=5, max_q=4, seasonal=True, m=7)
# Forecast
y_arima_exog_forecast = arima_model.predict(n_periods=365, exogenous=exog_to_tes
t)
```

In [14]:

```
print(arima_model.summary())
```

```
                                      SARIMAX Results                                      
==================================================================
=========================
Dep. Variable:                                     y   No. Observat
ions:                1097
Model:             SARIMAX(5, 0, 4)x(0, 0, [1, 2], 7)   Log Likeliho
od             -13556.462
Date:                            Thu, 26 Nov 2020   AIC                          
27146.925
Time:                                    10:58:48   BIC                          
27231.931
Sample:                                01-01-2015   HQIC                         
27179.087
                                     - 01-01-2018                                         
Covariance Type:                                opg                                         
==================================================================
==========
                 coef    std err          z      P>|z|      [0.025      
0.975]
------------------------------------------------------------------
----------
intercept   3.948e+05     23.209    1.7e+04      0.000    3.95e+05    
3.95e+05
sin30       -120.8237   4430.854     -0.027      0.978   -8805.137    
8563.490
cos30       5435.5531   3959.816      1.373      0.170   -2325.543    
1.32e+04
sin30_2     1.632e+04   4266.555      3.825      0.000    7956.422    
2.47e+04
cos30_2     1.824e+04   4089.864      4.460      0.000    1.02e+04    
2.63e+04
ar.L1          1.1469      0.061     18.684      0.000       1.027       
1.267
ar.L2         -0.6679      0.151     -4.431      0.000      -0.963      
-0.372
ar.L3         -0.2208      0.184     -1.201      0.230      -0.581       
0.139
ar.L4          0.0511      0.129      0.395      0.692      -0.202       
0.304
ar.L5          0.1147      0.047      2.427      0.015       0.022       
0.207
ma.L1         -0.8432      0.068    -12.469      0.000      -0.976      
-0.711
ma.L2          0.2704      0.128      2.115      0.034       0.020       
0.521
ma.L3          0.6196      0.127      4.885      0.000       0.371       
0.868
ma.L4         -0.1607      0.068     -2.356      0.018      -0.294      
-0.027
ma.S.L7        0.1071      0.033      3.246      0.001       0.042       
0.172
ma.S.L14      -0.0382      0.037     -1.021      0.307      -0.111       
0.035
sigma2      3.253e+09      0.034   9.55e+10      0.000    3.25e+09    
3.25e+09
==================================================================
===============
Ljung-Box (Q):                      178.69   Jarque-Bera (JB):               
26.19
```

```
Prob(Q):                              0.00   Prob(JB):
0.00
Heteroskedasticity (H):               0.98   Skew:
-0.30
Prob(H) (two-sided):                  0.86   Kurtosis:
3.45
====================================================================
===============

Warnings:
[1] Covariance matrix calculated using the outer product of gradient
s (complex-step).
[2] Covariance matrix is singular or near-singular, with condition n
umber 2.71e+26. Standard errors may be unstable.
```

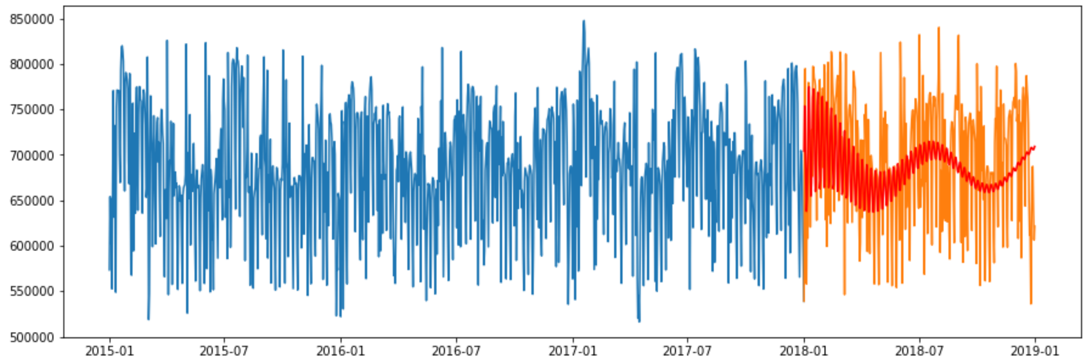
In [19]:

```
print(arima_model.conf_int())
```

```
                      0             1
intercept  3.947374e+05  3.948284e+05
sin30     -8.805137e+03  8.563490e+03
cos30     -2.325543e+03  1.319665e+04
sin30_2    7.956422e+03  2.468101e+04
cos30_2    1.022665e+04  2.625862e+04
ar.L1      1.026620e+00  1.267246e+00
ar.L2     -9.633684e-01 -3.724779e-01
ar.L3     -5.810089e-01  1.394193e-01
ar.L4     -2.022050e-01  3.044400e-01
ar.L5      2.205852e-02  2.073961e-01
ma.L1     -9.757332e-01 -7.106560e-01
ma.L2      1.982579e-02  5.209620e-01
ma.L3      3.710298e-01  8.682041e-01
ma.L4     -2.942986e-01 -2.702591e-02
ma.S.L7    4.244832e-02  1.718035e-01
ma.S.L14  -1.114907e-01  3.510819e-02
sigma2     3.252994e+09  3.252994e+09
```

In [16]:

```
# Predicted load on test data
y_preds = pd.Series(data = y_arima_exog_forecast, index = daily_test.index)

# Plot data
fig, ax = plt.subplots(figsize = (15,5))
#ax.plot(arima_model.y_hat, color = 'blue')
ax.plot(daily_train)
ax.plot(daily_test)
ax.plot(y_preds, color = 'red');
```



In [18]:

```
def show_metrics(y_true, y_preds):
    scores = {'MAE':mean_absolute_error(y_true, y_preds),
              'MSE': mean_squared_error(y_true, y_preds),
              'R2': r2_score(y_true, y_preds)}
    return scores

show_metrics(daily_test, y_preds)
```

Out[18]:

```
{'MAE': 54630.289649449005,
 'MSE': 4301793990.321909,
 'R2': 0.0017328987050304612}
```

SARIMA does not scale well in long-term prediction

TBATS

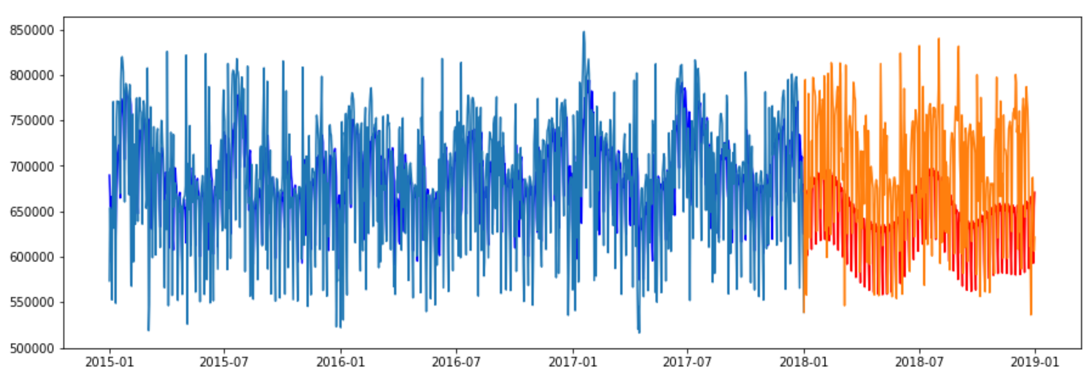
In [19]:

```
# We have 2016 is a leap year so yearly seasonality is 365.25
estimator = TBATS(seasonal_periods=(7, 365.25))   #provide the different seasona
lilties in seasonal_periods
tbats_model = estimator.fit(daily_load[:"2018-01-01"]) #processing time is too l
arge for this dataset and
# Forecast 365 days ahead
y_forecast = tbats_model.forecast(steps=365)
print(tbats_model.summary())
```

```
Use Box-Cox: False
Use trend: False
Use damped trend: False
Seasonal periods: [   7.    365.25]
Seasonal harmonics [3 4]
ARMA errors (p, q): (0, 0)
Smoothing (Alpha): 0.151820
Seasonal Parameters (Gamma): [ 0.00190774  0.00104656  0.00432327 -
0.00384274]
AR coefficients []
MA coefficients []
Seed vector [ 6.62139212e+05  2.51565943e+04 -3.92712359e+03 -4.0062
7389e+03
 -2.36826727e+04  1.72150585e+04 -7.34603415e+03  4.03627802e+03
  1.73682687e+04 -9.63167552e+03 -1.45507306e+03  1.95135198e+02
  1.59979522e+04 -3.32803458e+03  1.74731068e+03]

AIC 31724.647071
```

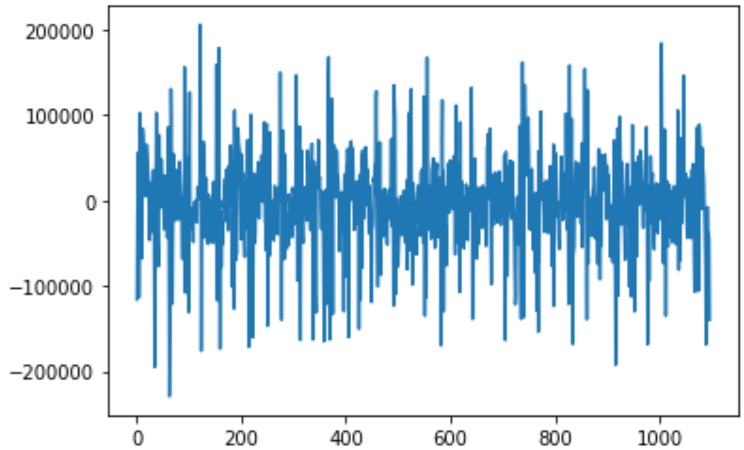
In [20]:

```
# Predicted load on training data
y_hat = pd.Series(data = tbats_model.y_hat, index = daily_train.index)
# Predicted load on test data
y_preds = pd.Series(data = y_forecast, index = daily_test.index)
# Plot data
fig, ax = plt.subplots(figsize = (15,5))
ax.plot(y_hat, color = 'blue')
ax.plot(y_preds, color = 'red')
ax.plot(daily_train)
ax.plot(daily_test);
```



In [14]:

```
# Plot the resid
plt.plot(tbats_model.resid);
```



In [21]:

```
show_metrics(daily_train, y_hat)
```

Out[21]:

```
{'MAE': 41107.56831231884, 'MSE': 3188007525.495207, 'R2': 0.2728351
233410876}
```

In [22]:

```
show_metrics(daily_test, y_preds )
```

Out[22]:

```
{'MAE': 75333.13038381858, 'MSE': 7612530873.301953, 'R2': -0.766551
1518000272}
```

TBATS well addressed the seasonalities, but the error is too large here, leading to serious overfit