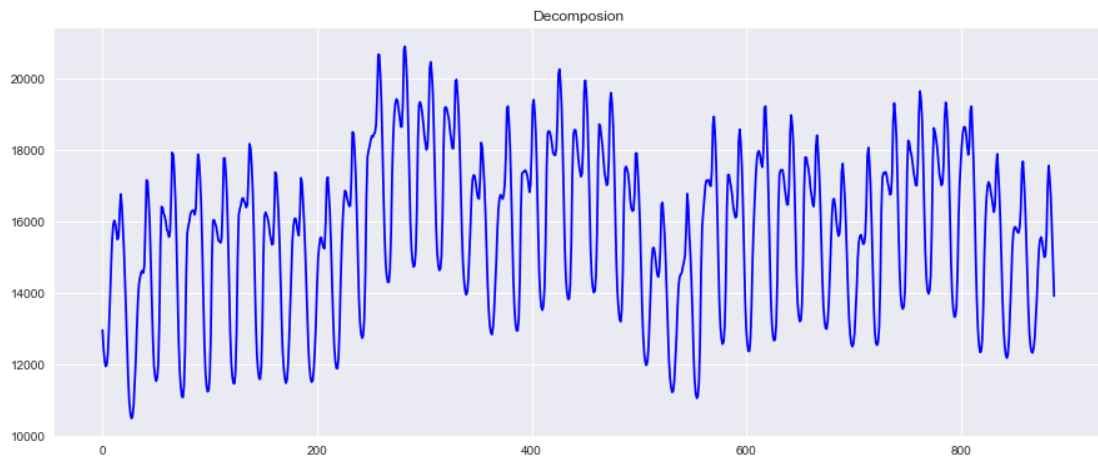


## A brief Report

### 1. Dataset

The System Load Data are derived from ISO New England Control Area within year of 2014.

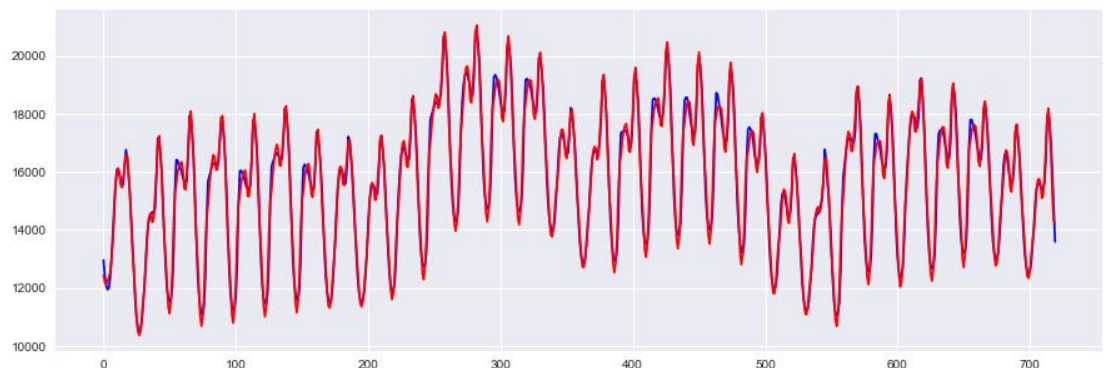
The graph below shows the actual hourly data from 2014/01/11 0:00 and followed with 720 + 168 hours in order to build the model and predict.



### 2. Steps of the algorithm

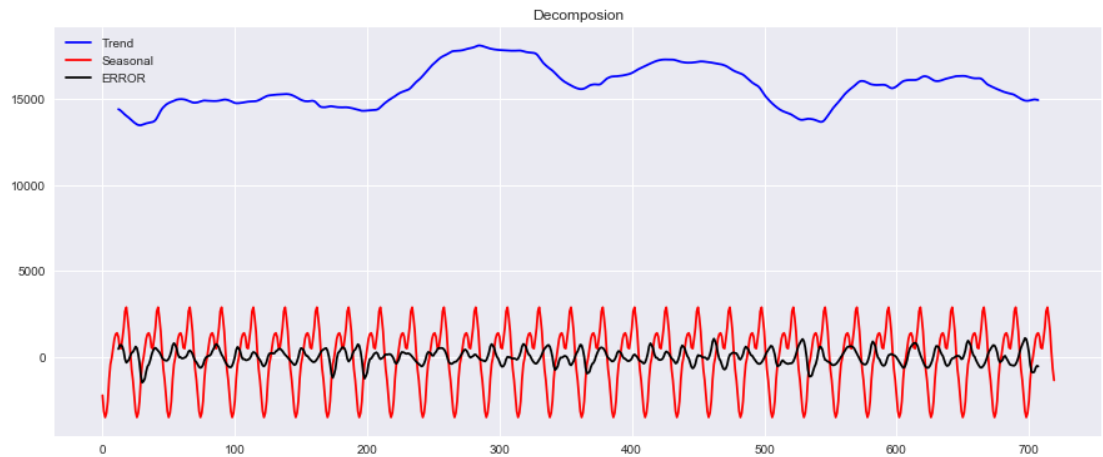
#### a) De-noise applied with wavelet

Though it is not essential here since the data is smooth enough, I do it otherwise.



#### b) Make a seasonal decompose 1<sup>st</sup> time

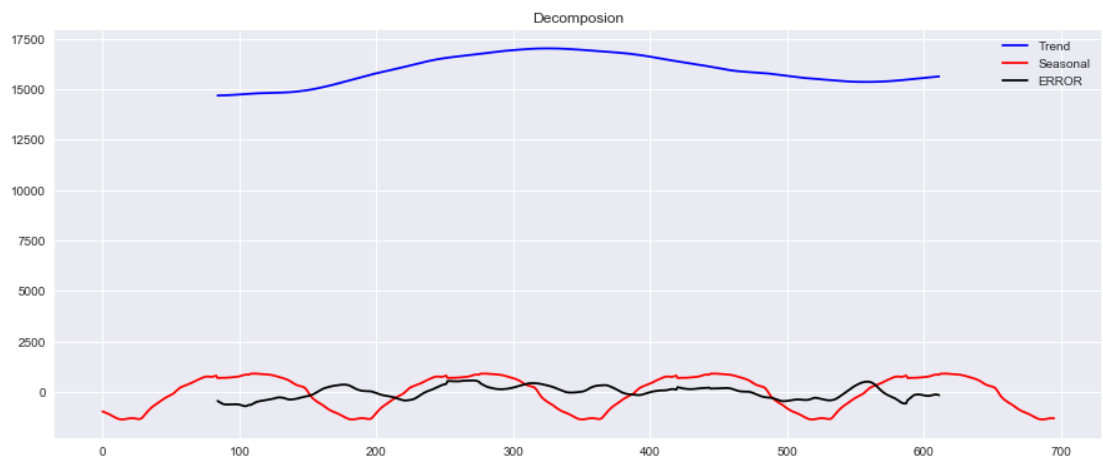
After the decomposing process, we gain the trends, the seasonal character and the error. I set the window to 24H, since it is obvious that there is any periodical fluctuation here.



Fortunately, The Error is not that large.

c) The 2<sup>nd</sup> Decomposing

There should be some information hiding in the trend curves. i.e., the 7\*24H periodicity. Decomposing for the 2<sup>nd</sup> time!



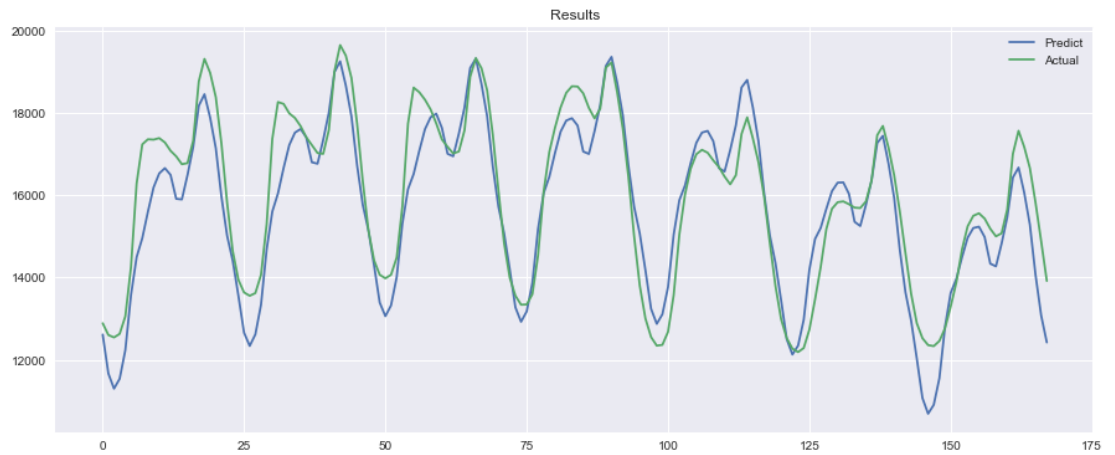
The result is acceptable, and the 7\*24H periodicity lies here. People work mostly on weekdays.

d) Make a naïve predict of the trend

If the interval of the predicted time is not that long, we can naively assume that the change of the trend is linear. Thus, just Draw a line.

e) Assemble these features

Sum them up.



f) Notes

The decomposing process using the function **seasonal\_decompose()** from **statsmodels.tsa.seasonal**.

The author says

#### Notes

This is a naive decomposition. More sophisticated methods should be preferred.

The additive model is  $Y[t] = T[t] + S[t] + e[t]$

The multiplicative model is  $Y[t] = T[t] * S[t] * e[t]$

The seasonal component is first removed by applying a convolution filter to the data. The average of this smoothed series for each period is the returned seasonal component.

### 3. Error