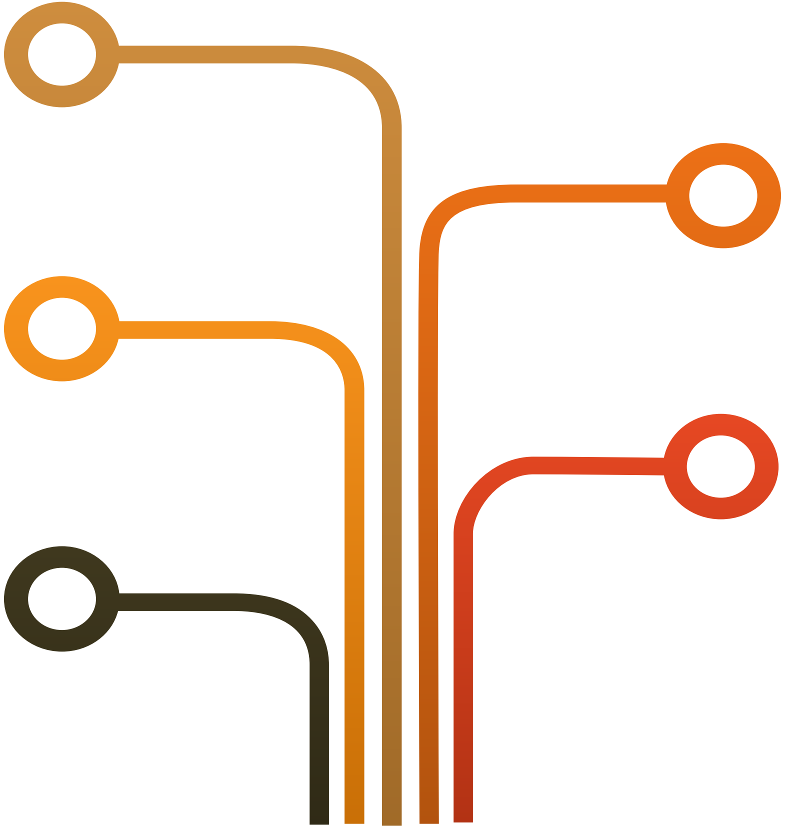
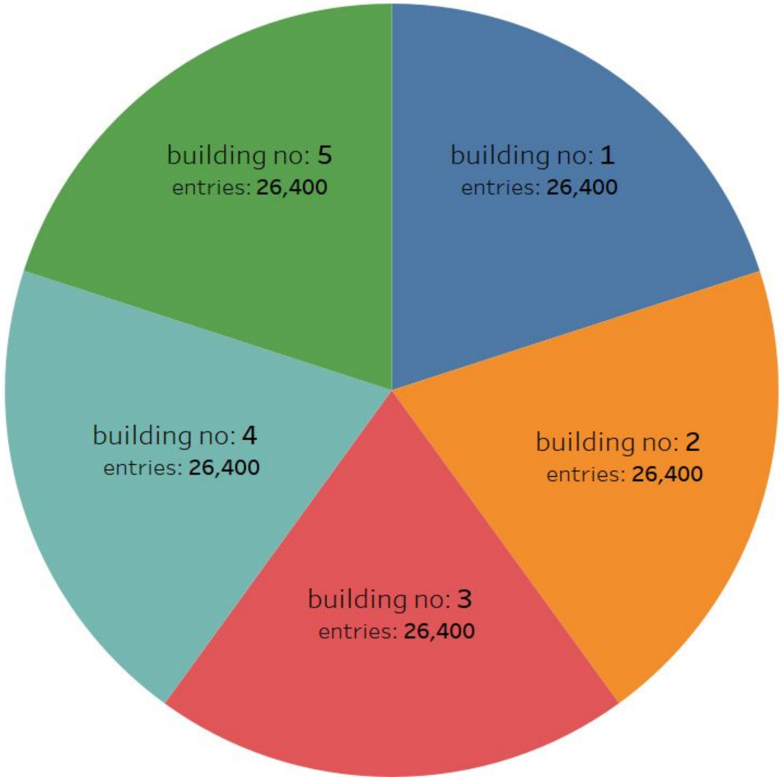

TEAM 9
WATTHOUR METER
SINGLE PHASE 2-WIRE
220 V
15(45) A
50 Hz

01 Stages of Data Analysis

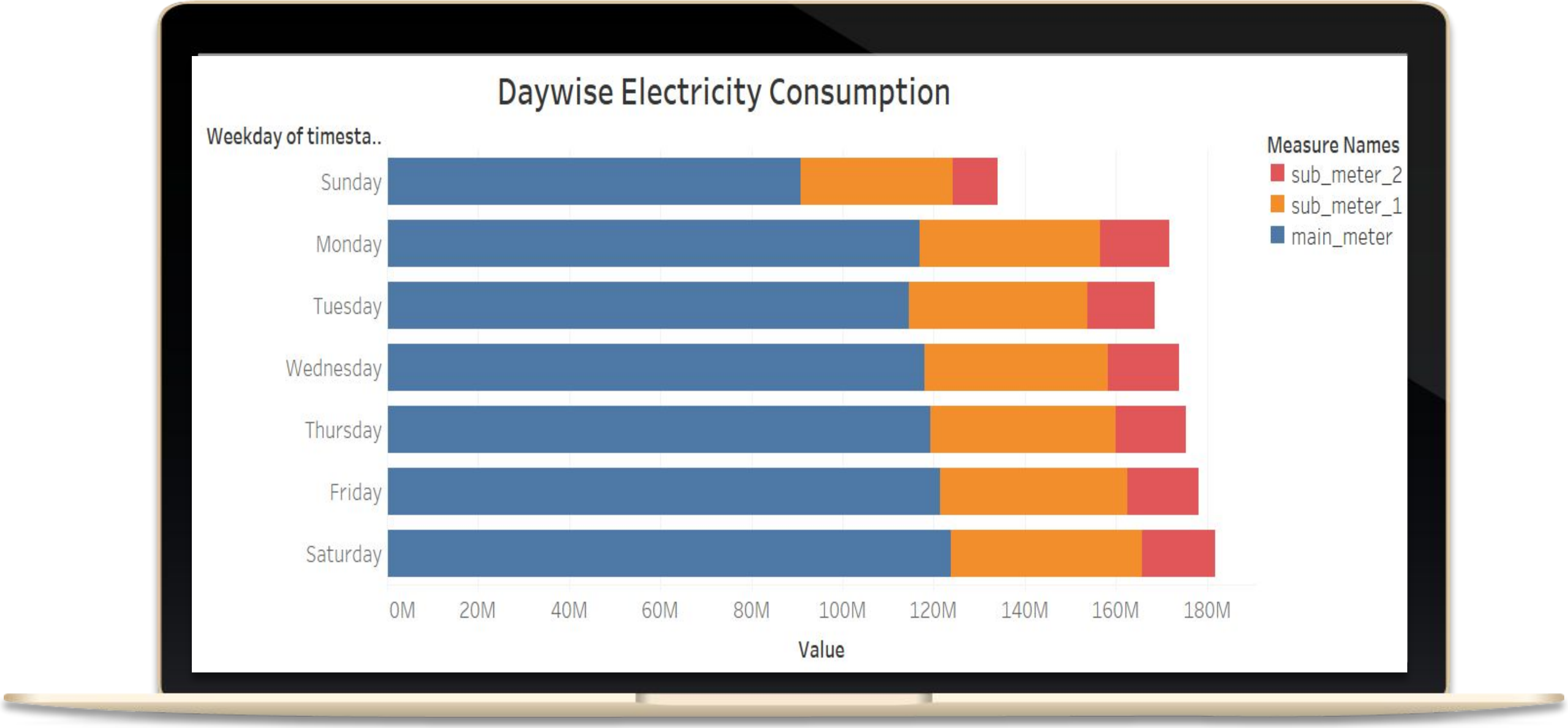


02 Data Distribution of Different Buildings



Number of Meter Entries per Building

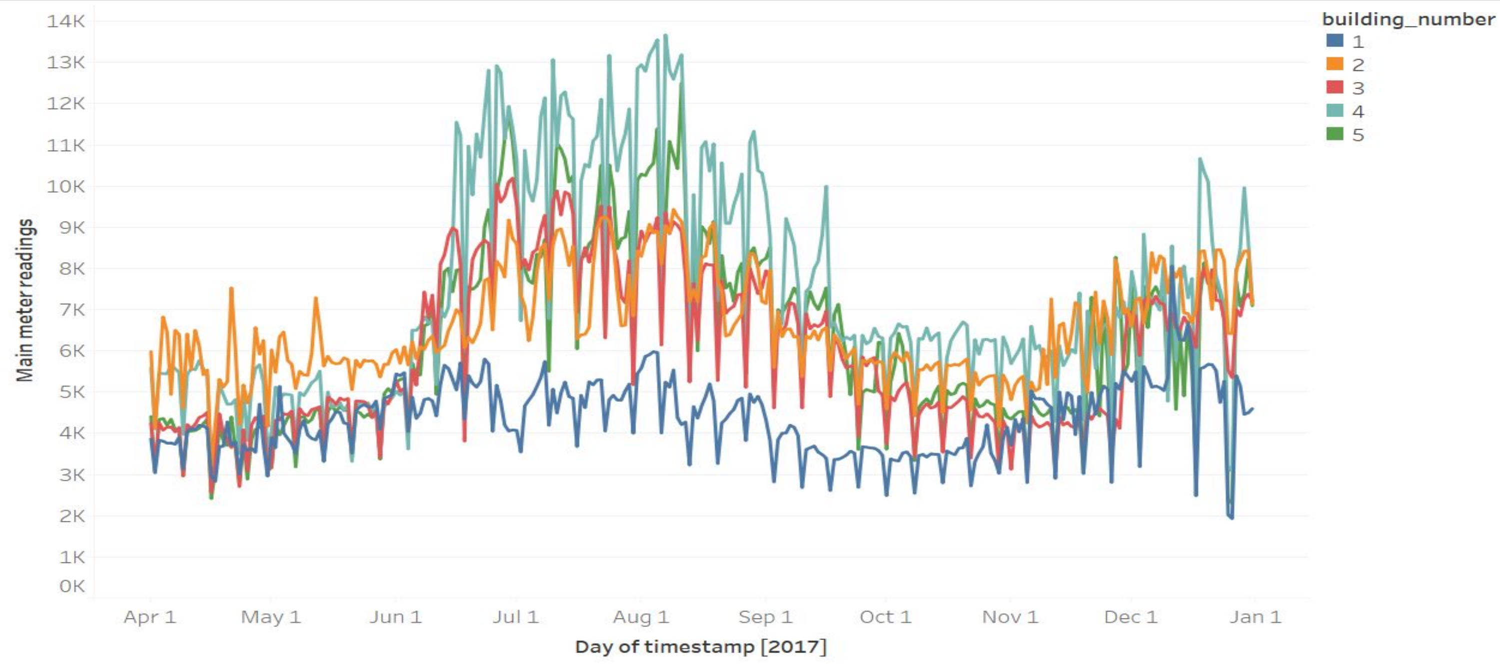
03 Exploratory Data Analysis



04 Exploratory Data Analysis

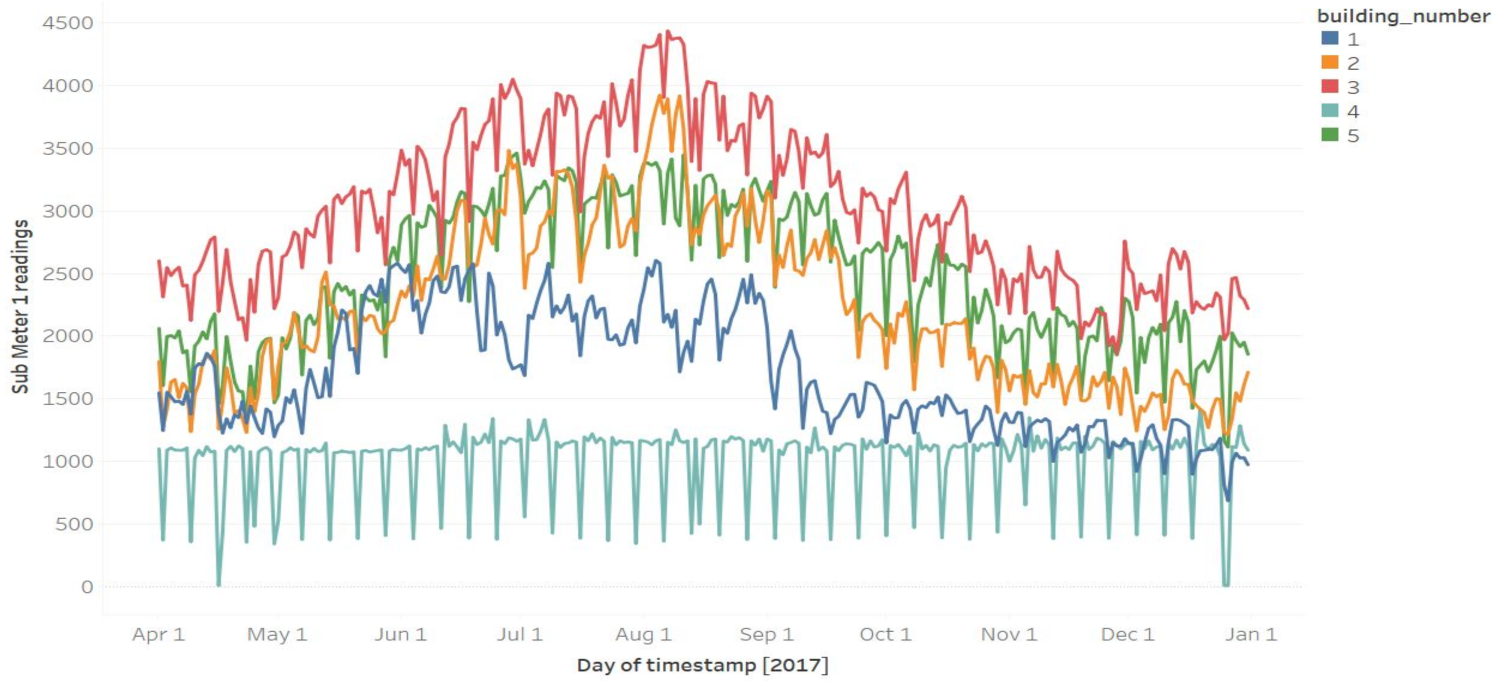
05 Exploratory Data Analysis

Day-Wise Main-Meter Readings

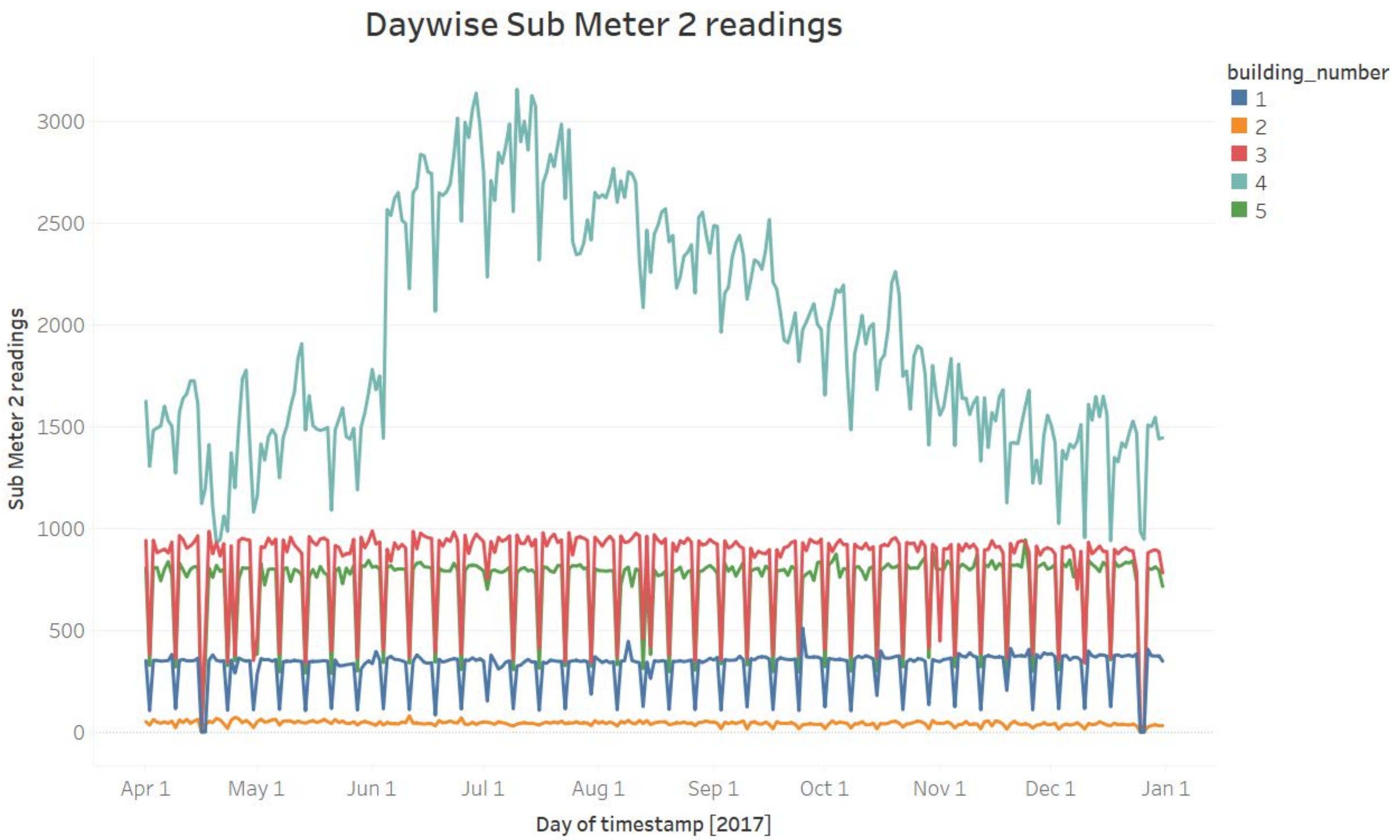


Exploratory Data Analysis

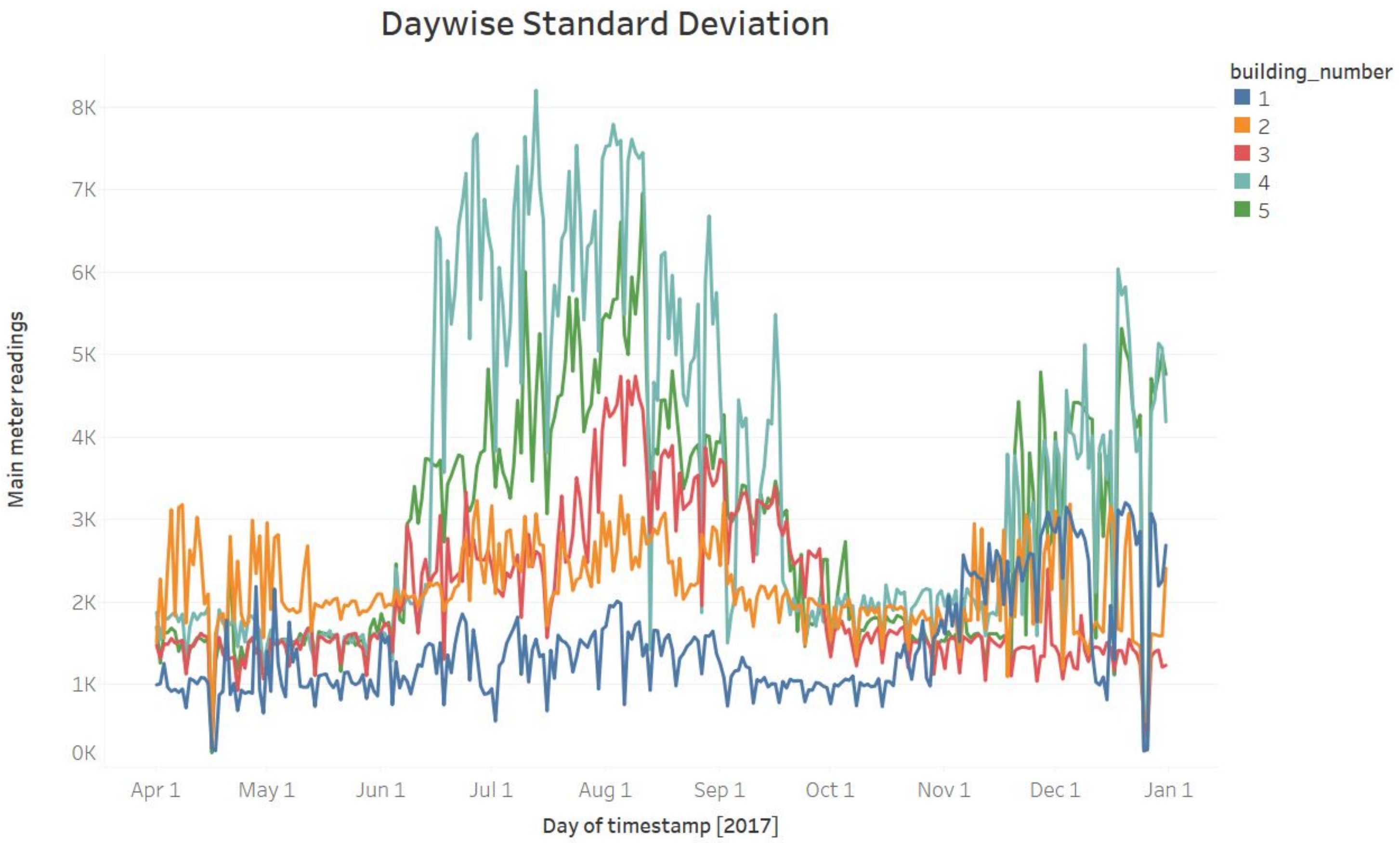
Day-Wise Main-Meter Readings



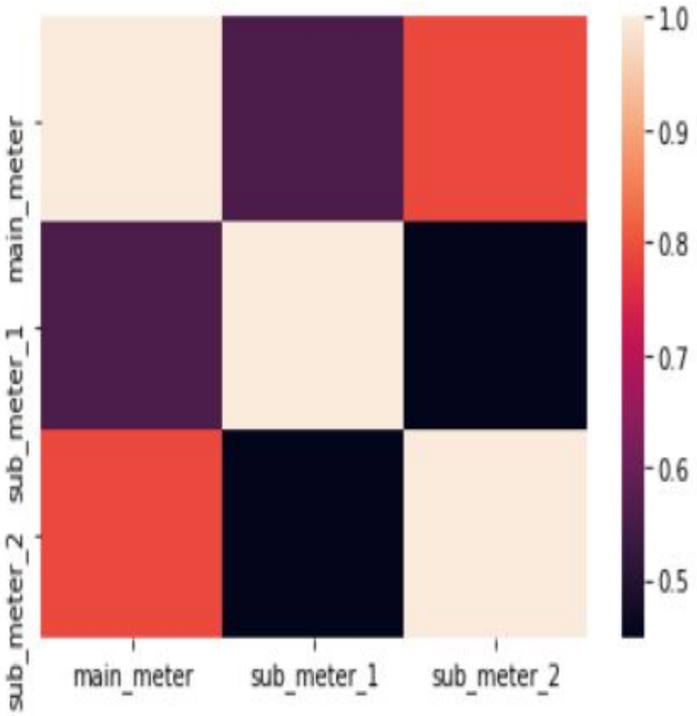
Exploratory Data Analysis



Exploratory Data Analysis



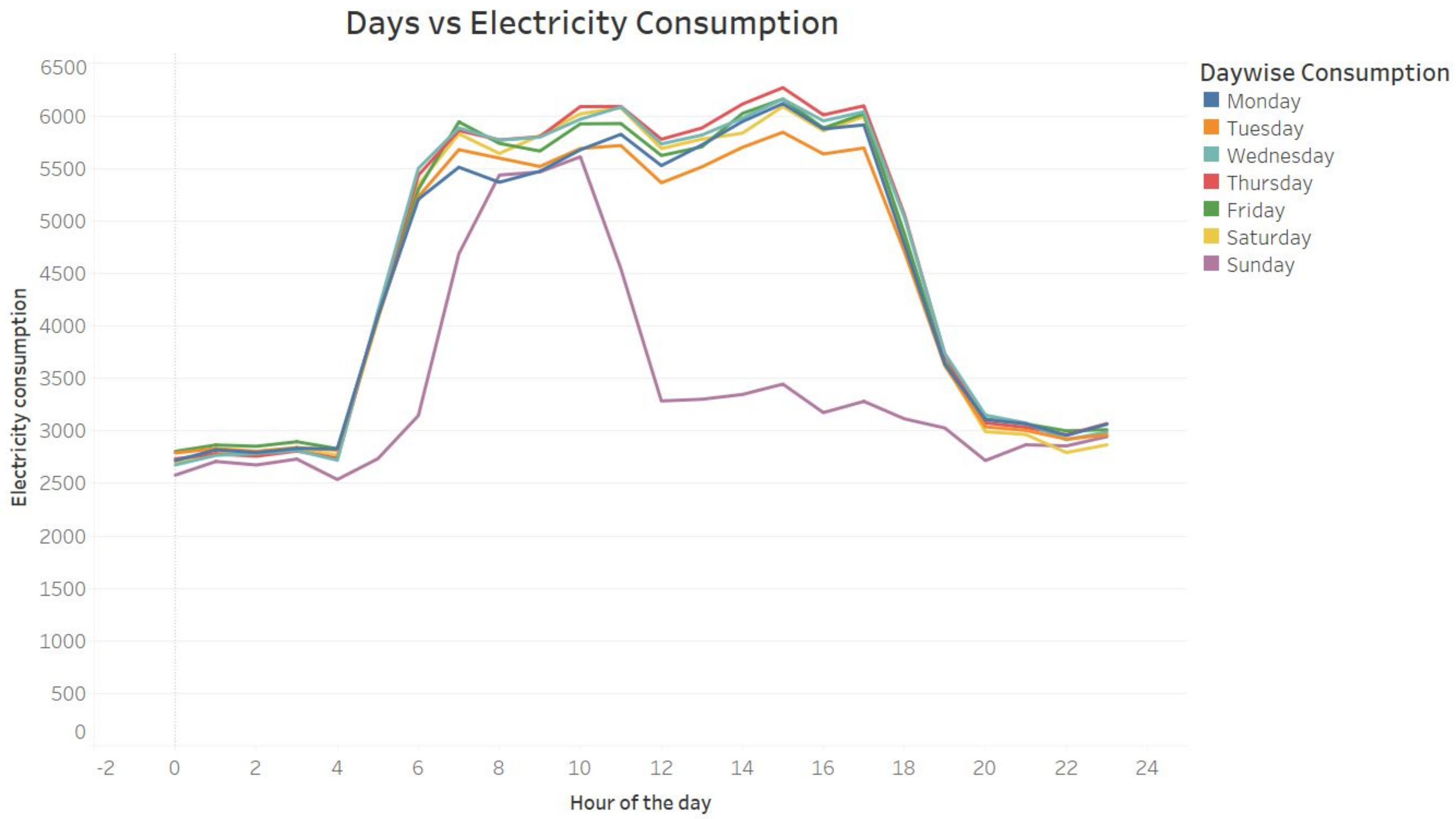
Exploratory Data Analysis



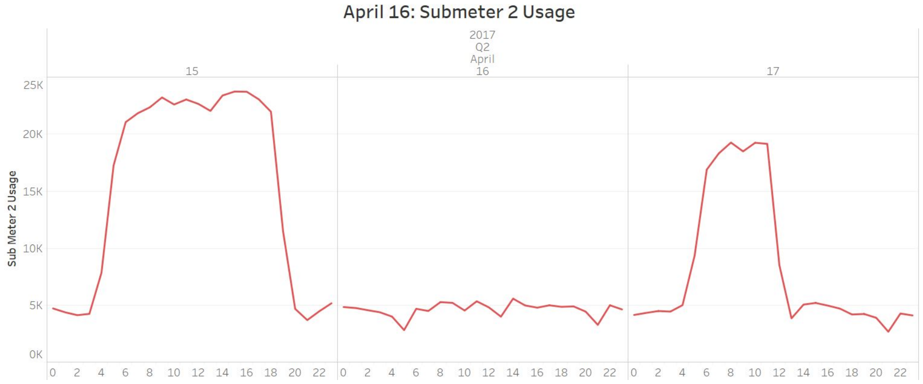
Correlation between Meters

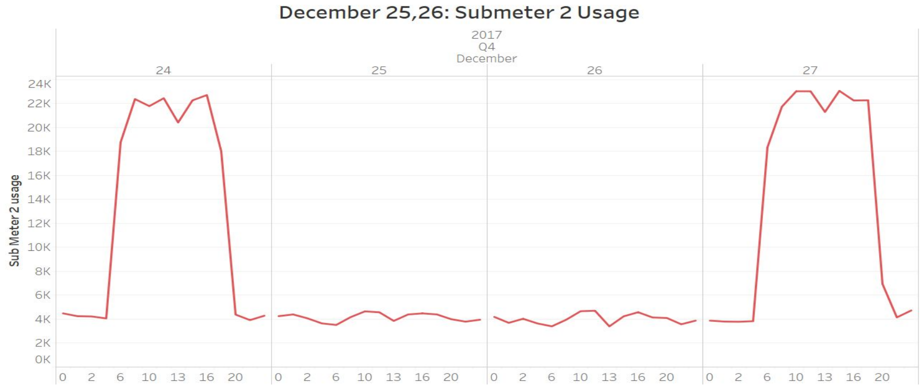
We can see that the correlation value between all the meters are above 0.5 for a building, the increase and the decrease is taking place at nearly same time for all three meters. So we decided to use the same model for all three meters.

Exploratory Data Analysis



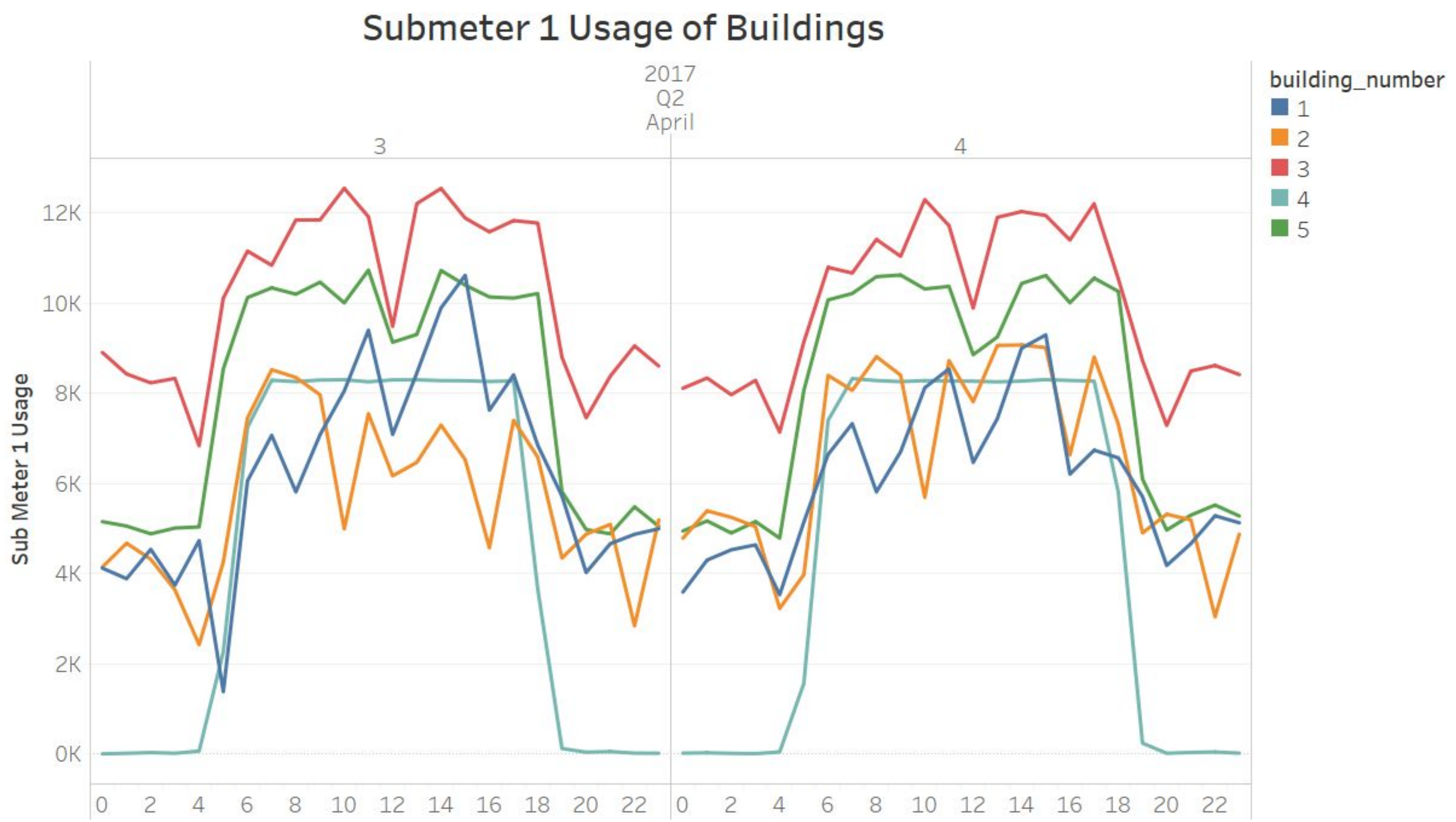
Exploratory Data Analysis



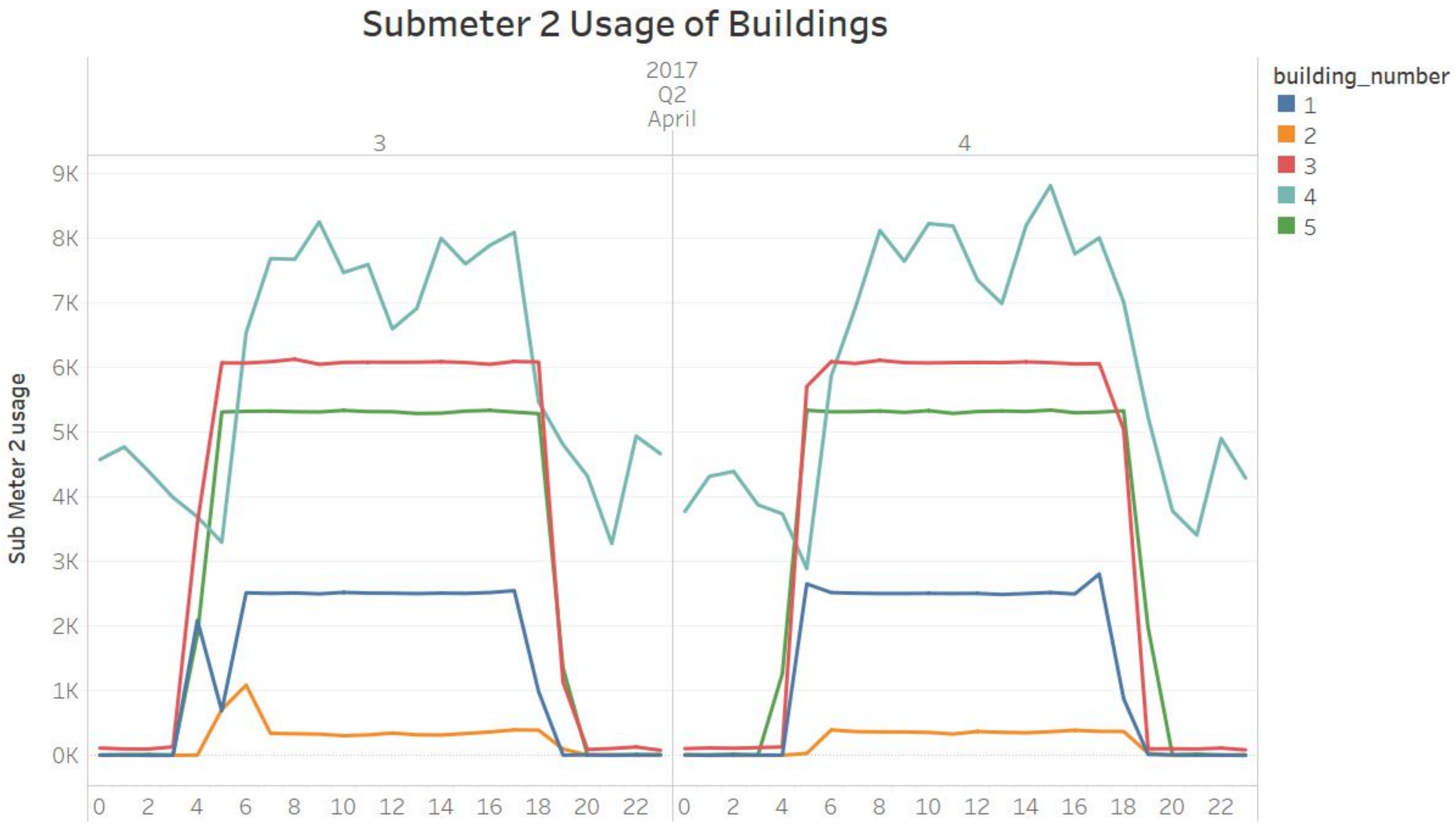


Time series shows daily seasonality with some exception of sundays.But this seasonality is broken in 3 days by a large margin. On these days peak usage during day is absent and usage is residual usage. These days could be holidays for company (Christmas and Easter fall on these days)

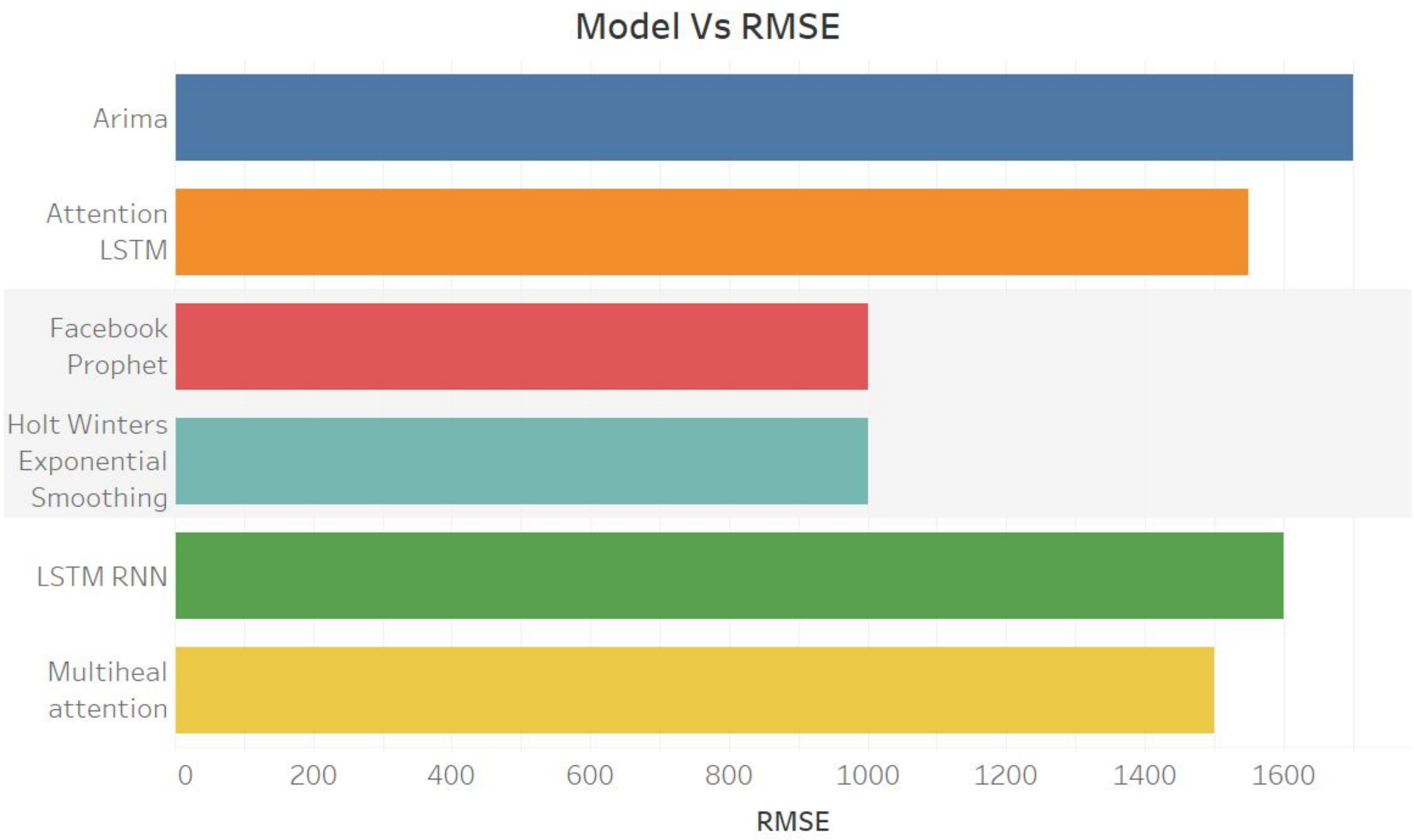
Exploratory Data Analysis



Exploratory Data Analysis



Exploratory Data Analysis



1. **Holt-Winters forecasting Method**

The Holt-Winters forecasting algorithm allows users to smooth a time series and use that data to forecast areas of interest. Exponential smoothing assigns exponentially decreasing weights and values against historical data to decrease the value of the weight for the older data. Holt Winters uses **Triple Exponential Smoothing** which is used for forecasting data with trend and/or seasonality.

There are two main HW models, depending on the type of seasonality:

- **Multiplicative Seasonal Model**

In this model time-series is assumed to be represented as:

$$y_t = (b_1 + b_2t)S_t + t$$

- **Additive Seasonal Model**

In this model the time series is assumed to be represented as:

$$y_t = b_1 + b_2t + S_t + t$$

Notations Used:

b_1: is the base signal also called the permanent component

b_2: is a linear trend component

S_t: is a multiplicative/additive seasonal factor

ε_t: is the random error component.

Introduction

Holt Winters Algorithms are applied when data is stationary.

Basically, there are three types of Holt Winters Exponential Smoothing methods :

1.Holt Winters Single Exponential Smoothing : Suitable for forecasting data with no trend or seasonal pattern. However level of the data may be changing over time as shown in figure 1

2.Holt Winters Double Exponential Smoothing : Suitable for forecasting data with trend as shown in figure 2.

3.Holt Winters Triple Exponential Smoothing : Suitable for forecasting data with trend and/or seasonality as shown in figure 2.

Figure 1

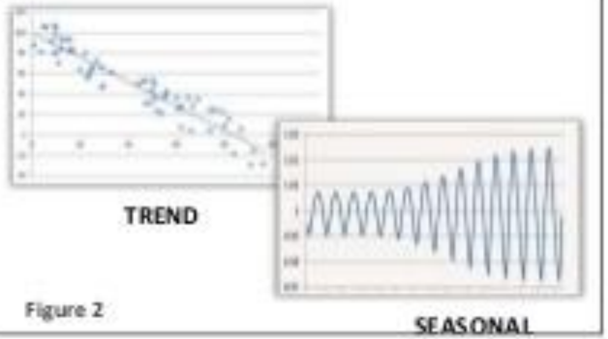


Figure 2

2. fb Prophet

The Prophet uses the a decomposable time series data mainly comprising of mainly three components namely seasonality, trend and holidays. They all are combined in the following manner:

g(t): piecewise linear or logistic growth curve for modeling non-periodic changes in time series.

s(t): periodic changes (e.g. weekly/yearly seasonality)

h(t): y(t)= g(t) + s(t) + h(t) + εt

effects of holidays (user provided) with irregular schedules

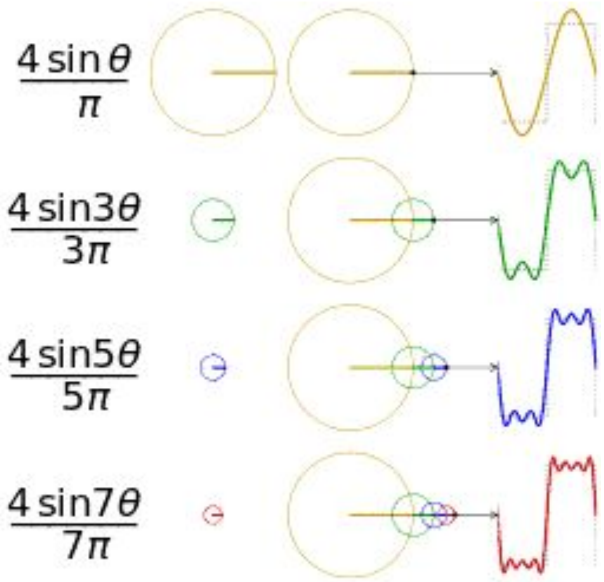
$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right)$$

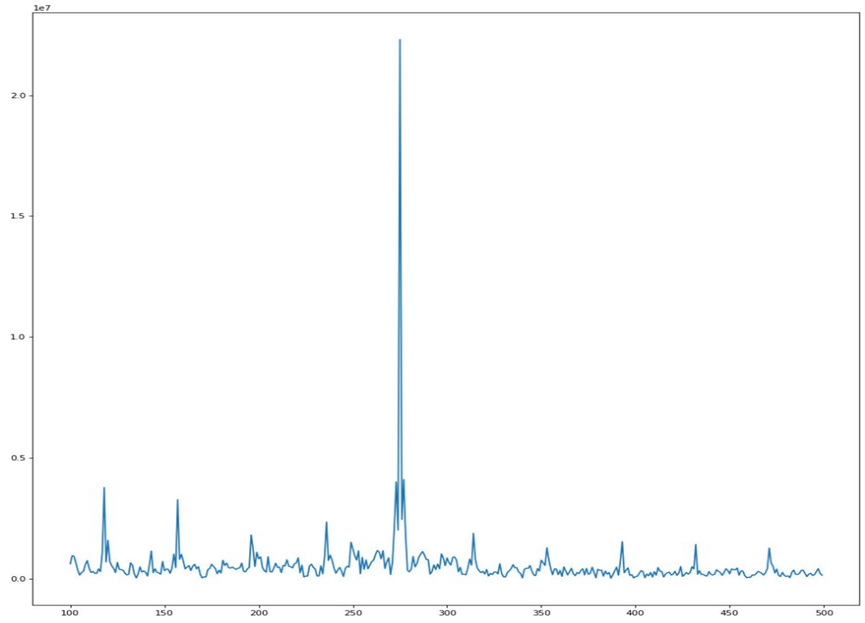
To fit and forecast the effects of seasonality, prophet relies on fourier series to provide a flexible model. Seasonal effects s(t) are approximated by the function given above:

We can treat time series as a signal. At the heart of any model trying to estimate a signal there basically lies some basic components:

1) A linear component capturing a trend in data

2) Other and more significant component is seasonal trend. Most models try to decompose a given signal into a fourier series. By altering the coefficients of sin and cos terms we can effictively decompose any periodic signal, these coefficients can be found by simple integral or in our case discrete time inverse fourier transform.





Finding Frequency Using Fast Fourier Transform:

We plotted the graphs of fast fourier transform(which is a discretized implementation of fourier transform) of the given dataset for building 1.

We saw a sudden increase at a data index around 280.

This behaviour was shown by other buildings giving maximum around 2nd or 3rd multiple of 96.

This can be explained by anomalies in time series listed before.

The anomaly on sundays is causing frequency to shift to higher values.

MODEL ARCHITECTURE

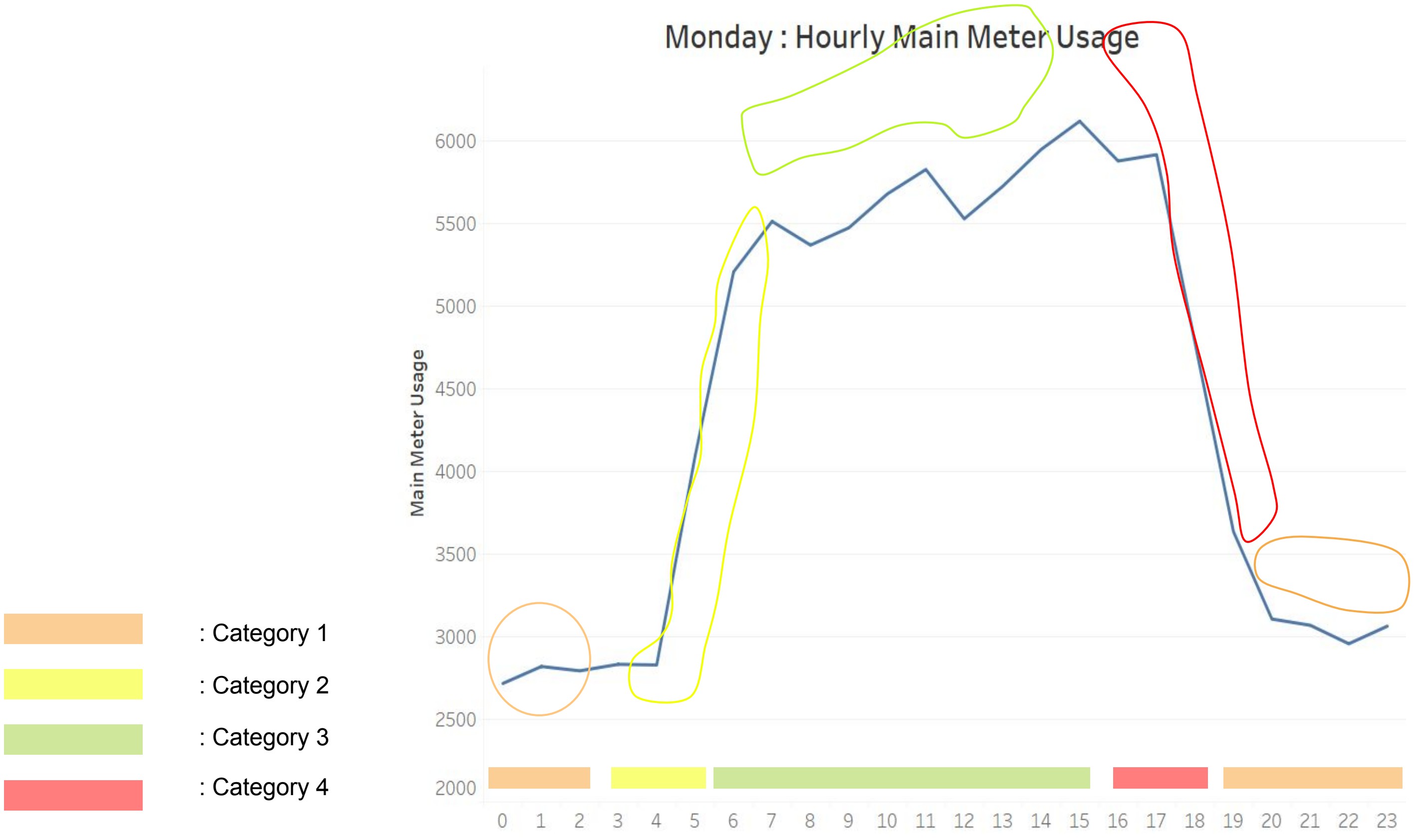
Our main focus was on Holt's Winter Exponential Smoothing and facebook's Prophet, since the results for these two better than other models. In Holt's Winter Exponential Smoothing the seasonal_periods parameter was set to 672 (96*7) to capture trends for whole week. This was later verified and found to be best parameter by using grid search.

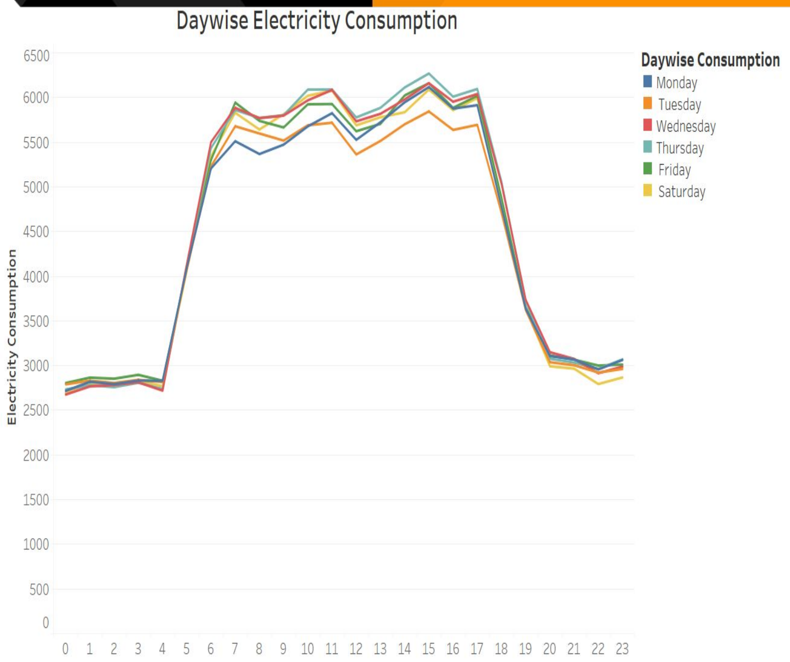
For facebook's Prophet we did grid search and found that peak values were obtained for setting seasonality parameters to multiples of 96. Prophet also has facility for additional regressor variable on which time series might depend. Two variables were added :

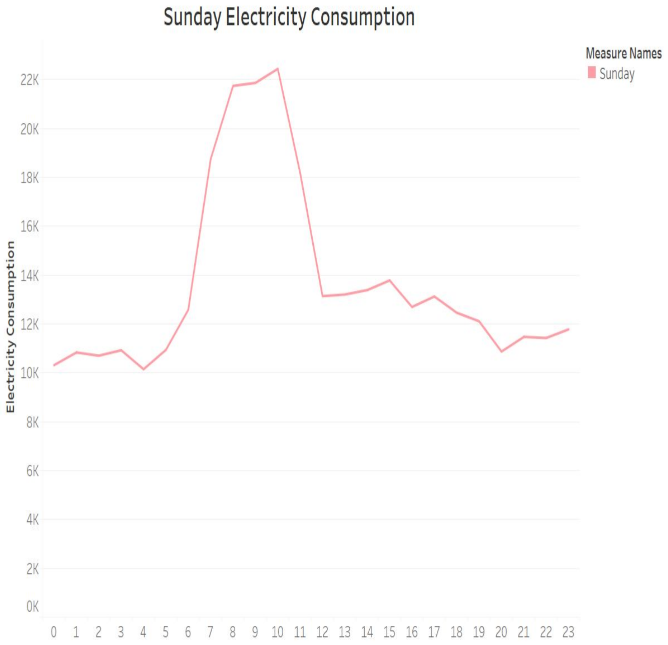
1) One variable representing the day of week
   This was done to properly capture the different behavior of data in sunday (peak values were obtained for lesser amount of time). All other days were set as 0 and sunday was set as 1.
1) The Other variable was hours
   Hours were label encoded. For hours 0, 1, 2, 19, 20, 21, 22, 23 the value was set to 1, for hours 6, 7, 8, 9, 10, 11, 12 , 13, 14, 15 value was set to 2, for hours 3, 4, 5 which indicated the upward transition was set to 3 and for 16, 17, 18 which indicated the downward and less steeper transition of value was set to 4 .

The custom seasonality was set to match the daywise periodicity.

It was also found model was predictions were more precise when periodic parameters were

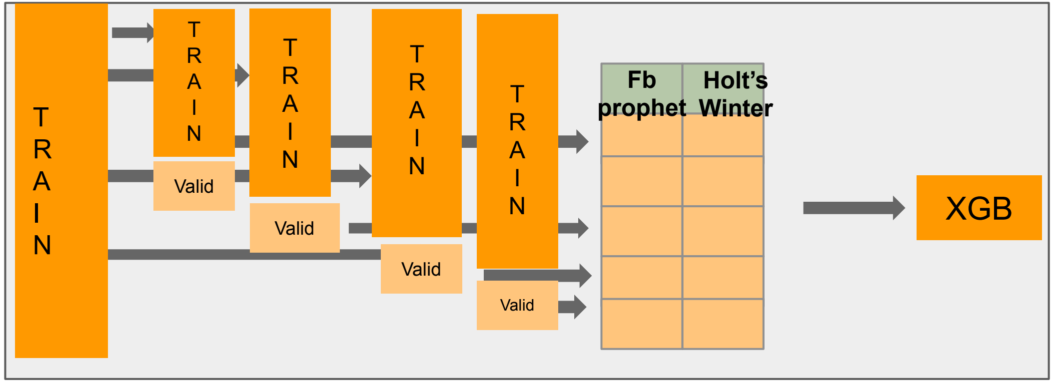

Monday : Hourly Main Meter Usage
Main Meter Usage
6000
5500
5000
4500
4000
3500
3000
2500
2000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
: Category 1
: Category 2
: Category 3
: Category 4





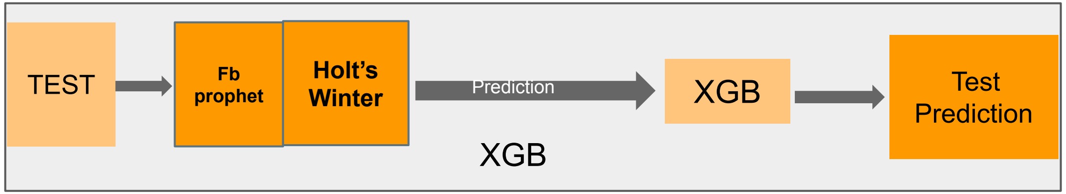
: Category 1

: Category 2



k-fold cross validation
training for base models

Training for
stacking regressor



Prediction basel
models

Prediction stacking
regressor

Evaluation Metric

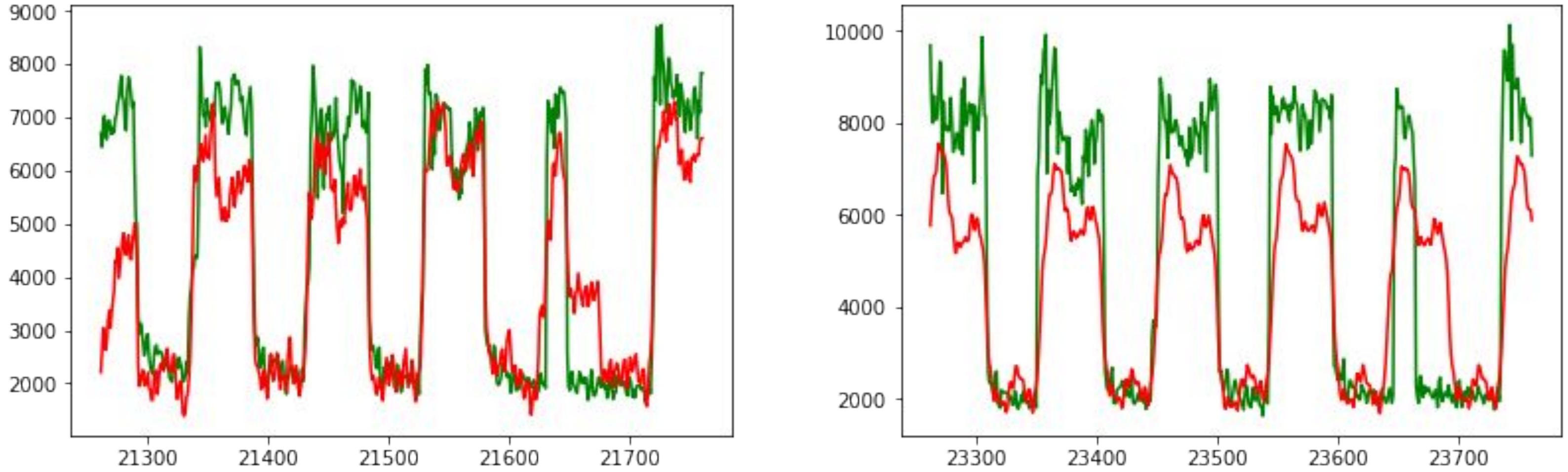
Simple Average across errors of all 5 buildings where error for a single building is calculated as

$$1/3\sum_{i=A}^{i=C}(1/\overline{m_i})\sqrt{\sum_{t=1}^{t=T}(m_{it}-\widehat{m_{it}})^2.e^{-kd(t)}}$$

Exponential term is basically added to down weight prediction further in future.When k is substituted in the equation and evaluated, this constant will reduce magnitude of squared error.This term doubles the tolerance for error every hundred days.

Some common sources of errors:

1) While adding rolling mean the the information of target is stored in rolling mean. This gives unusually high precision while predicting on validation dataset.
2) While working with sequential models at time of evaluation on validation dataset, instead of feeding ground truth values from validation to generate sequence for prediction, the sequence should generated by previously predicted values. And on this sequence a new value should be predicted, which will be merged with sequence for further predictions.



Predictions