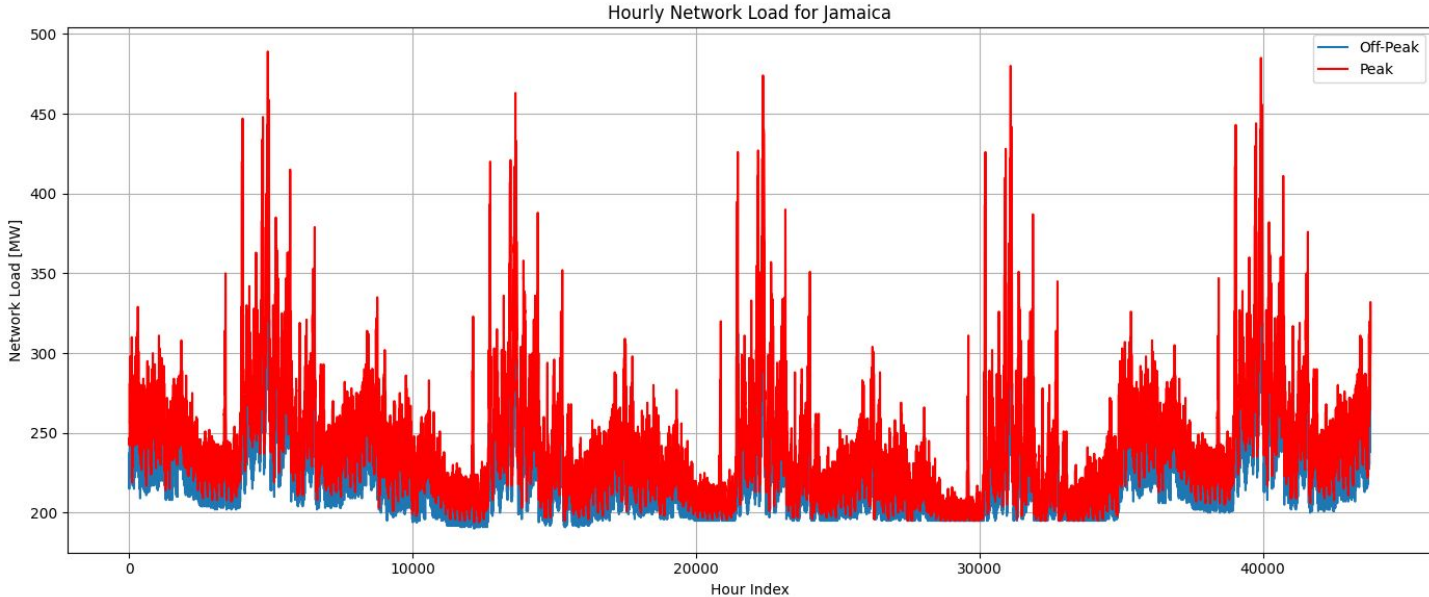


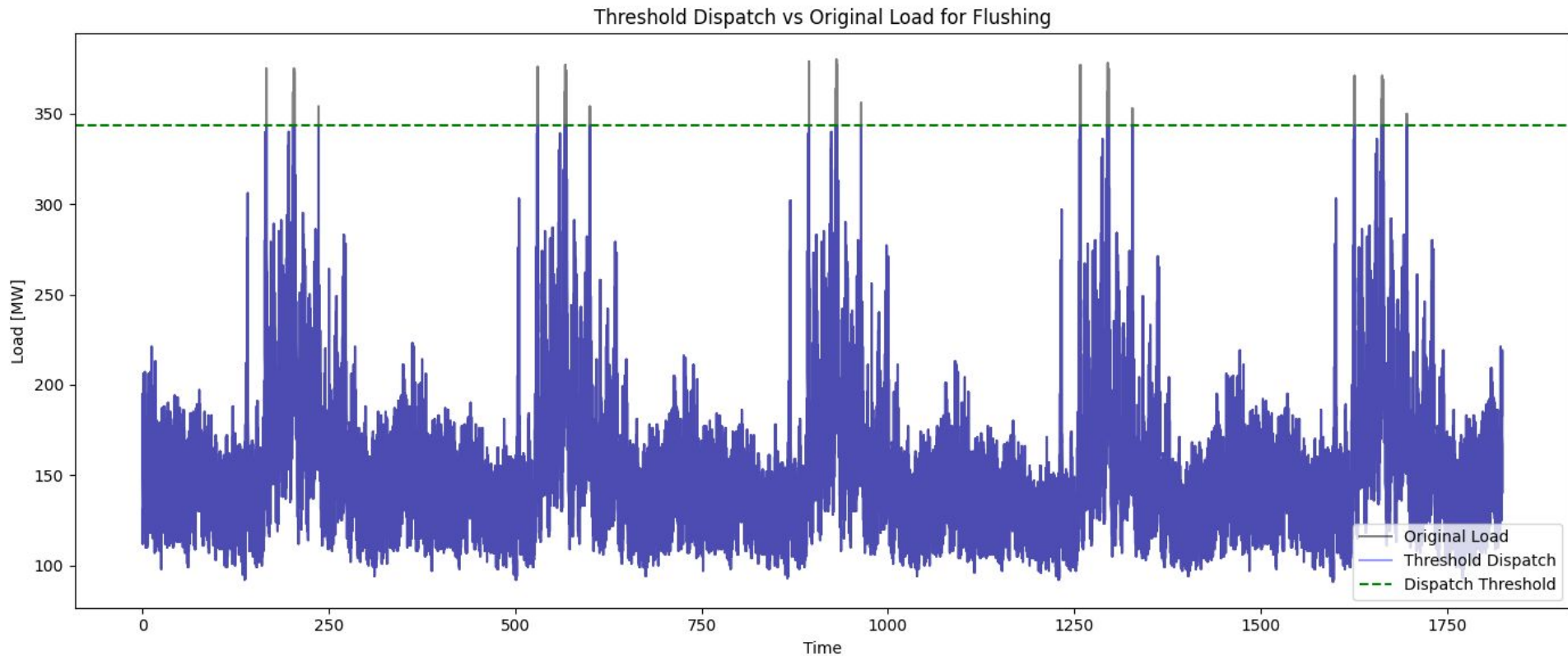
# DSC Final Project

Gautaman Asirwatham

# Problem

NYC's energy distribution system needs to be sized according to peak loads which is far greater than the average load.

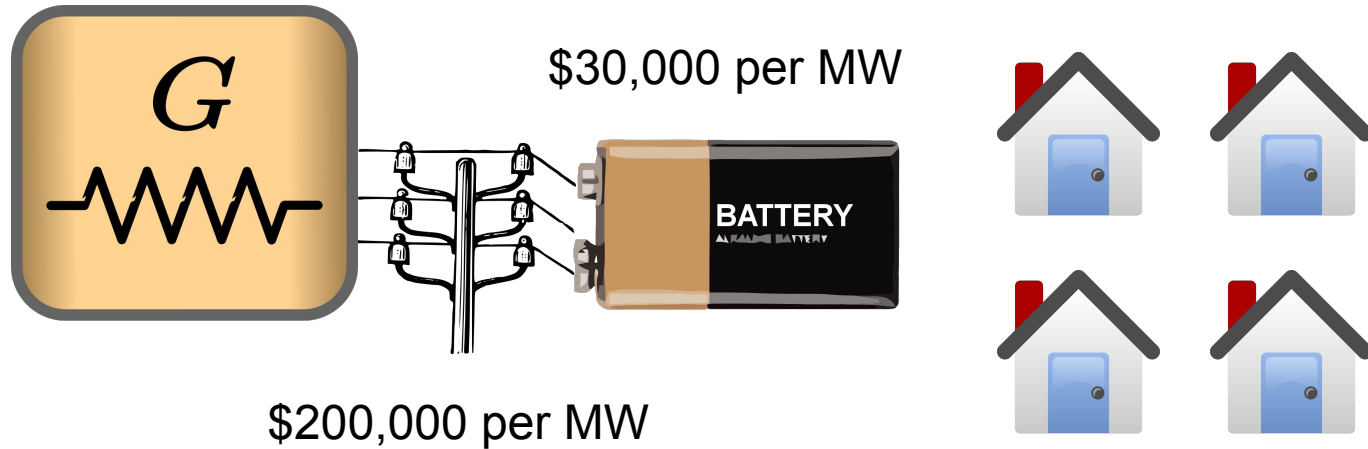




We can set the threshold of this controller according to our allowable failure rate.

# Hypothesis

A battery system can save money by lowering peak loads and deferring upgrades.



# My Dataset



# My Dataset 2

Time-of-Use Periods	PEAK RATES 8 A.M. TO MIDNIGHT	OFF-PEAK RATES ALL OTHER HOURS OF THE WEEK
JUNE 1 TO SEPT 30	<b>35.23 cents/kWh</b>	<b>2.49 cents/kWh</b>
ALL OTHER MONTHS	<b>13.05 cents/kWh</b>	<b>2.49 cents/kWh</b>

## Super-peak Pricing

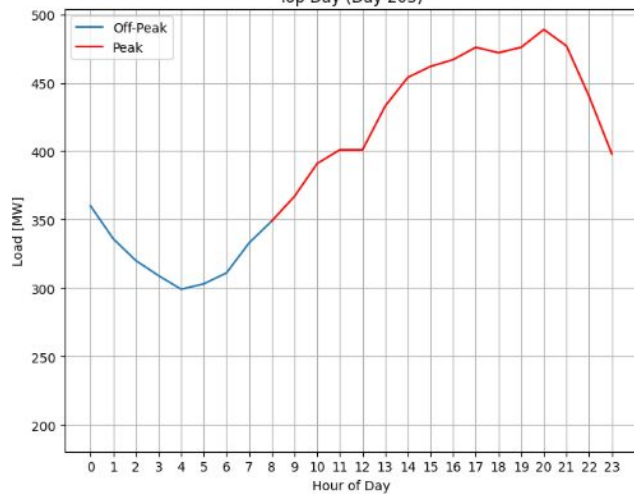
Electricity supply is an additional cost. Summer super-peak pricing is in effect from June through September on weekdays between 2 and 6 p.m. Super-peak charges are significantly higher than supply charges during the rest of the day. Save by opting to power down during super-peak periods.

Standard Delivery Periods	RATES <250 KWH	RATES >250 KWH
JUNE 1 TO SEPT 30	<b>16.107 cents/kWh</b>	<b>18.518 cents/kWh</b>
ALL OTHER MONTHS	<b>16.107 cents/kWh</b>	<b>16.107 cents/kWh</b>

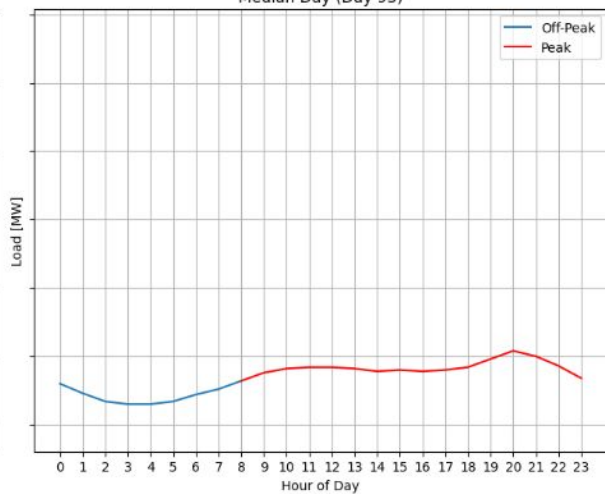
# EDA

Top, Median, and Bottom Days Load Profiles for Jamaica

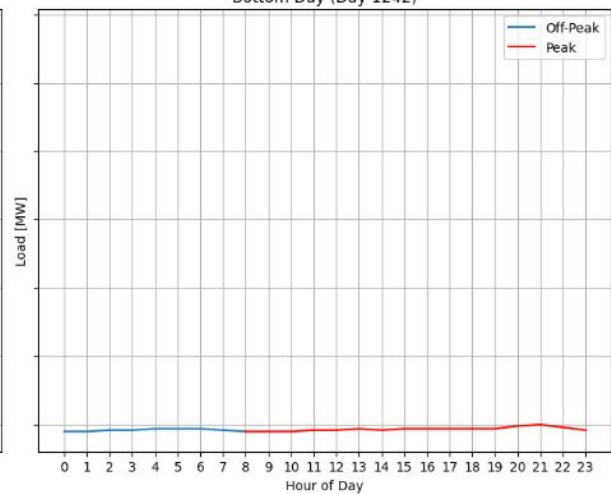
Top Day (Day 203)



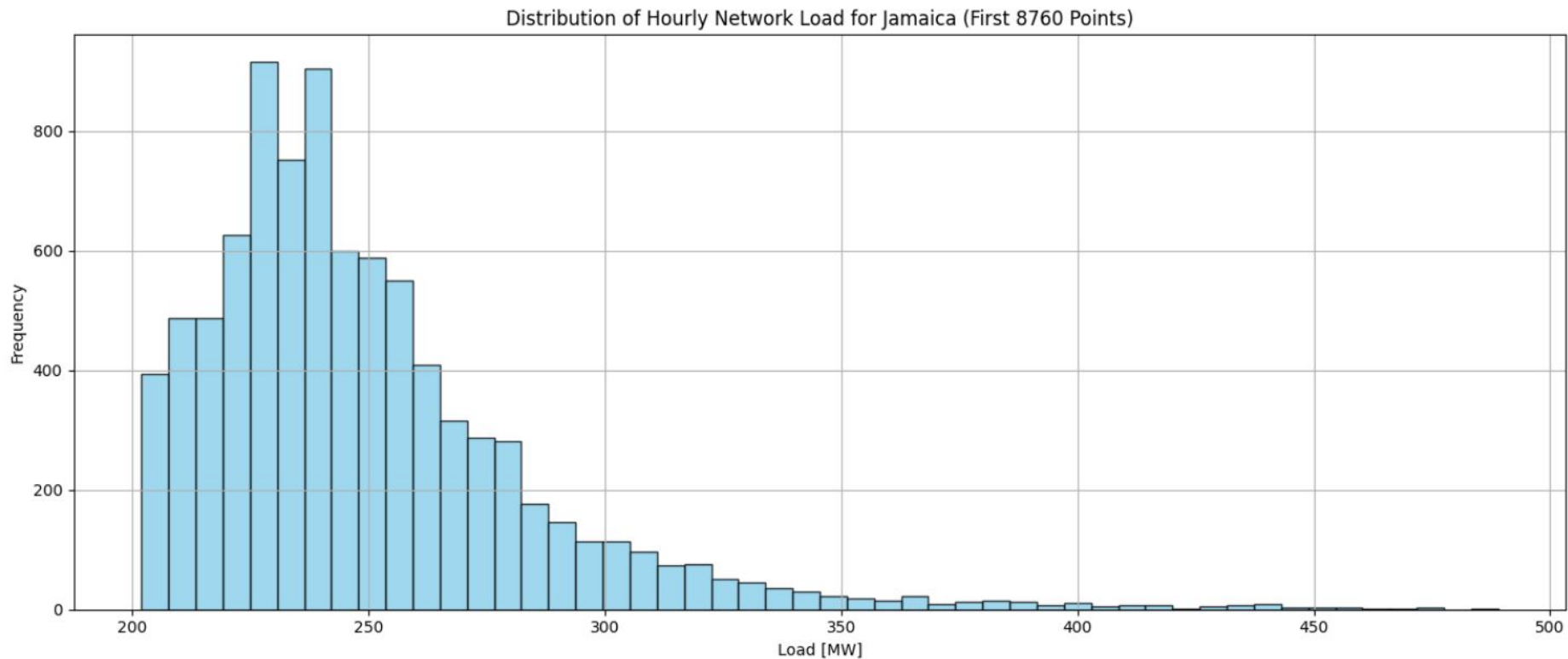
Median Day (Day 93)



Bottom Day (Day 1242)

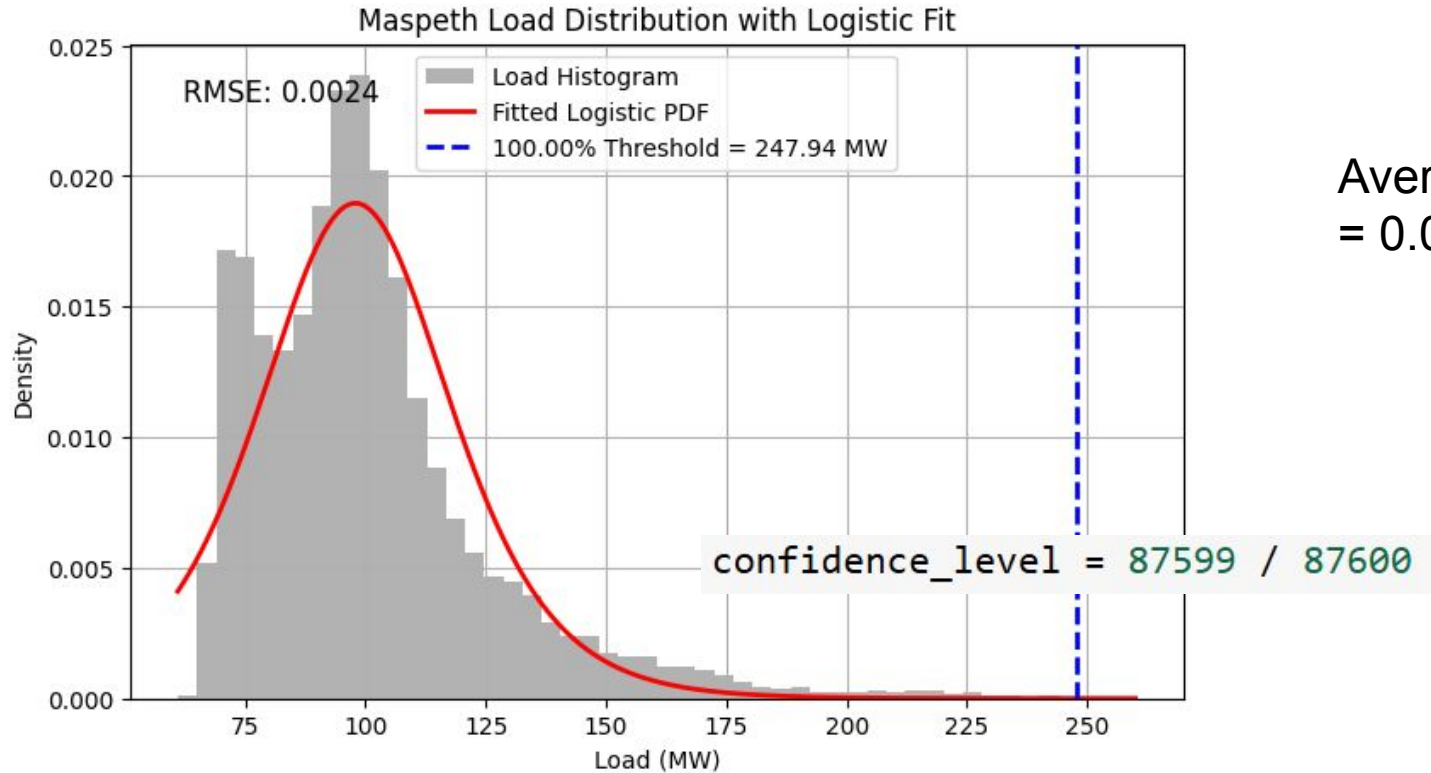


# EDA 2



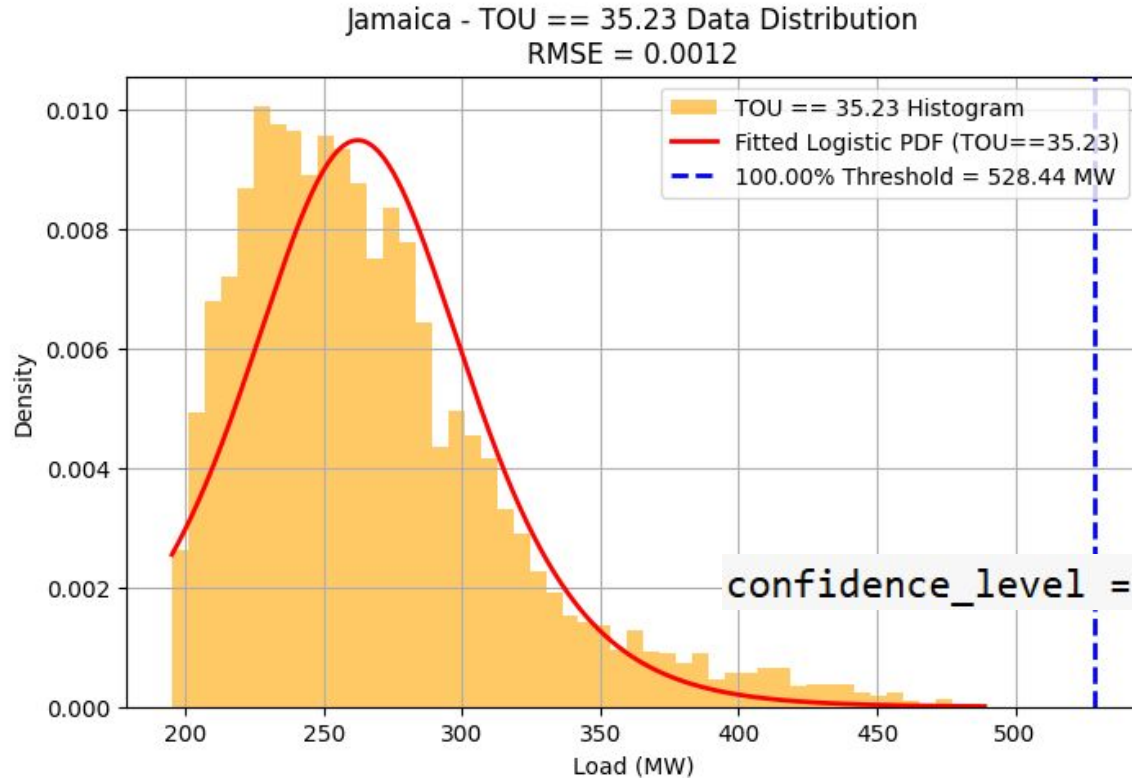


# Peak Estimation Model 1



Average RMSE  
= 0.0049

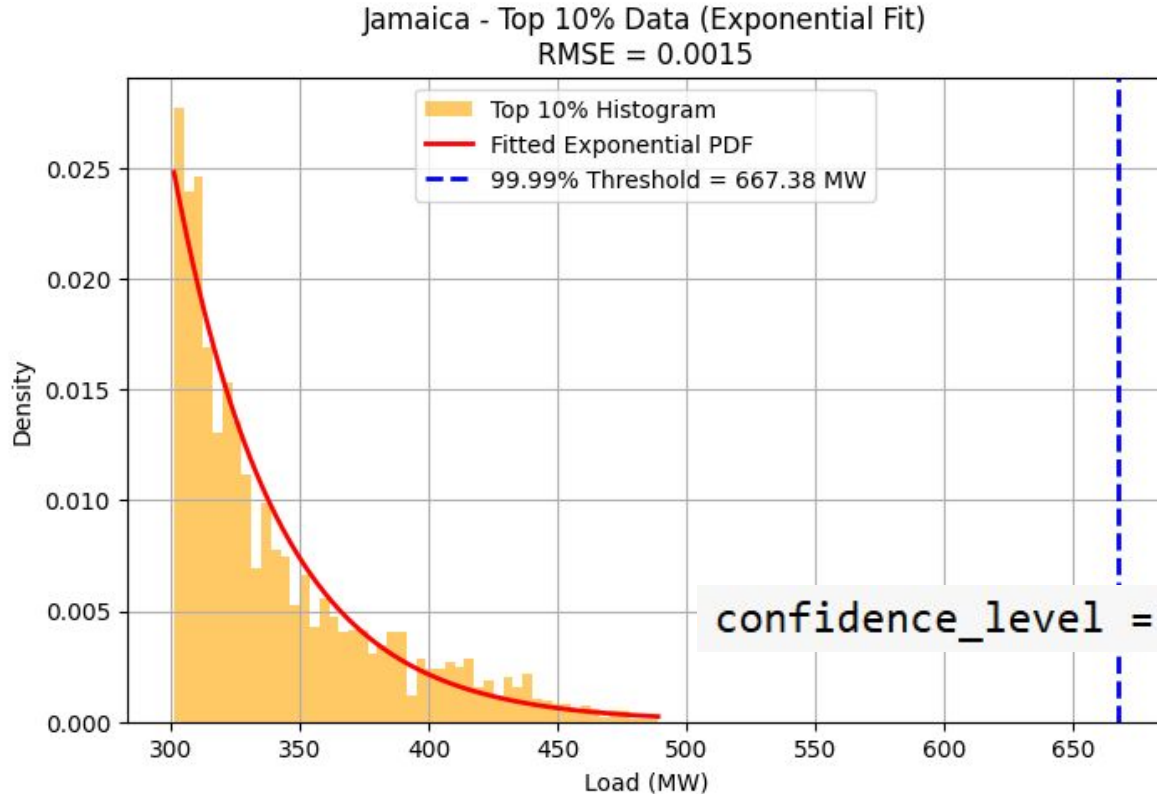
# Peak Estimation Model 2



Average RMSE = 0.0032

confidence\_level = 24399 / 24400

# Another cool model I tried



Average RMSE = 0.0070

# Battery Addressable Load Model 1

```
L_max = load_series.max()

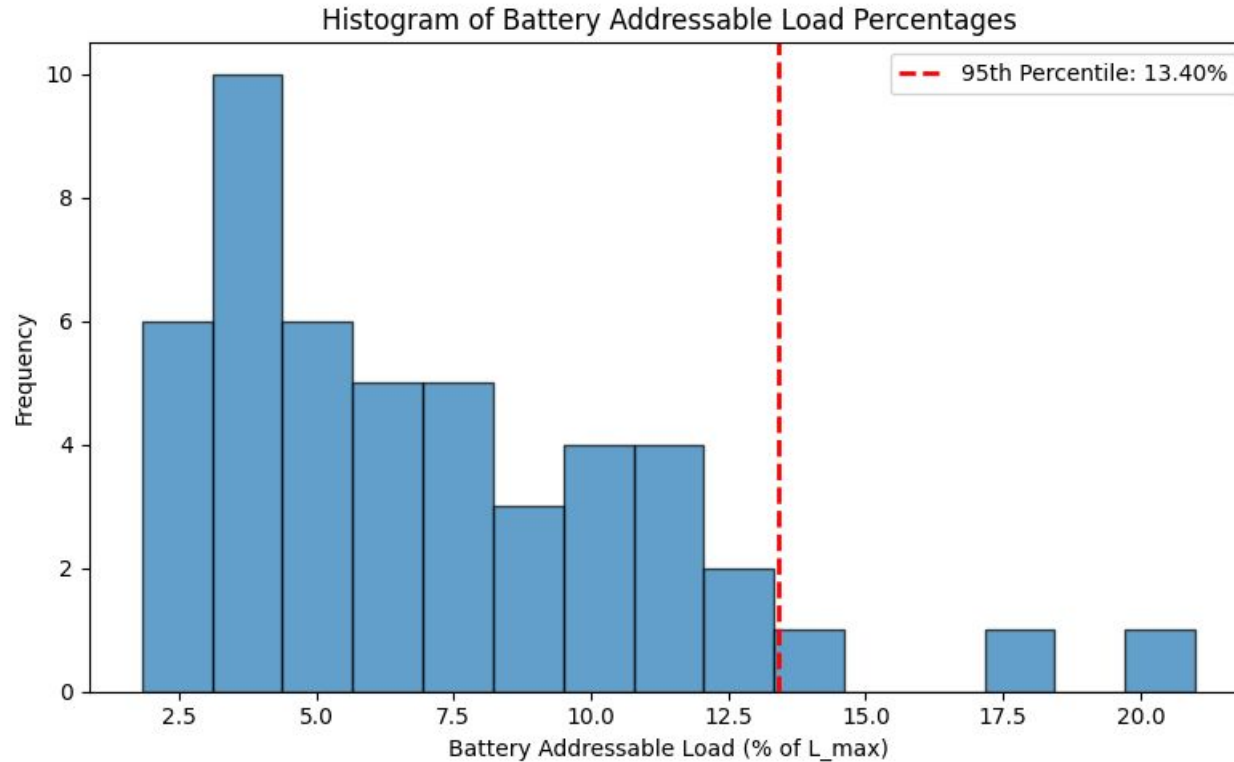
# Set lower bound to 90% of L_max and upper bound to L_max.
lb = 1e-6
ub = L_max

# Define g(x) = 4*x - max_daily_shaved_energy, where for each day,
# daily_shaved_energy = sum(max(0, load - (L_max - x)))
# and we use the maximum value across days.
def g(x):
    threshold = L_max - x
    # Compute the shaved energy for each day using the global loads_df day column.
    daily_shaved_sum = load_series.sub(threshold).clip(lower=0).groupby(loads_df['Day']).sum()
    max_daily_shaved = daily_shaved_sum.max()
    return 4 * x - max_daily_shaved
```

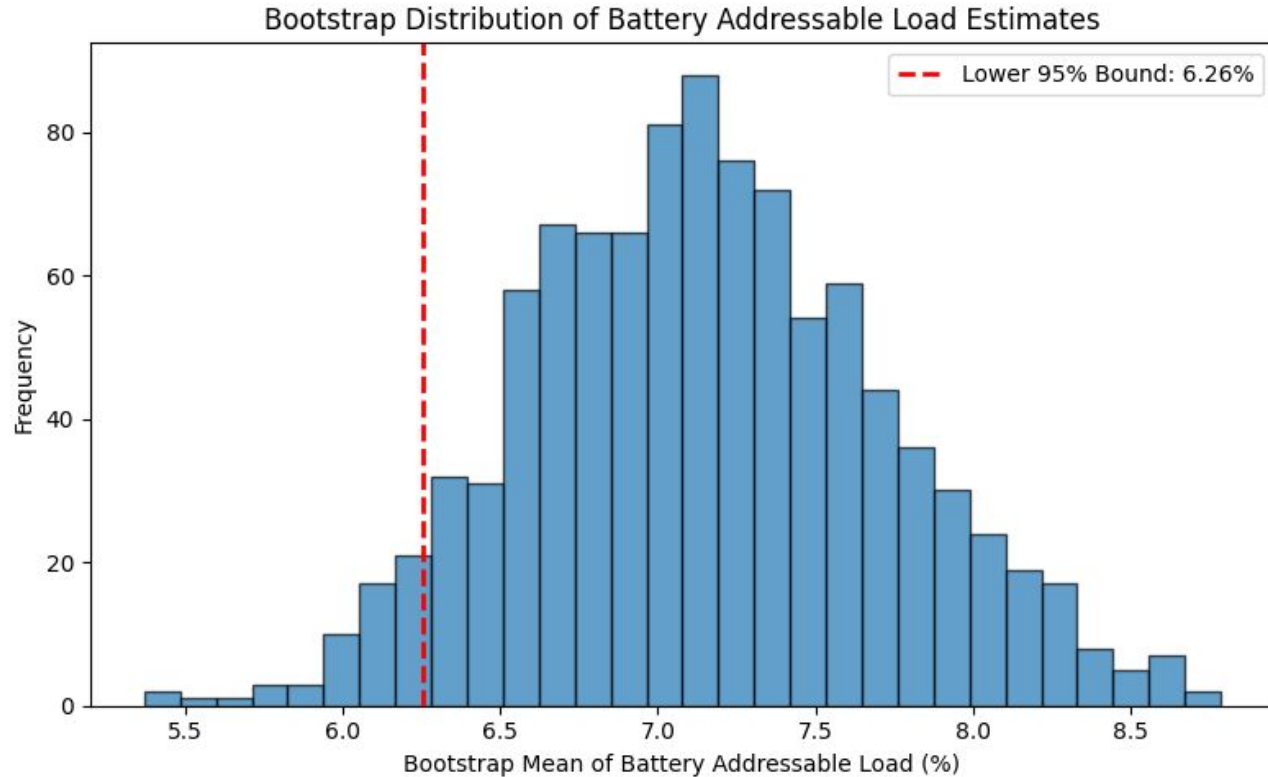
```
# Binary search: find the largest x
for _ in range(max_iter):
    mid = (lb + ub) / 2
    if g(mid) >= 0:
        lb = mid
    else:
        ub = mid
    if abs(ub - lb) < tol:
        break

x = lb
pct = (x / L_max) * 100
dispatch_threshold = L_max - x
return dispatch_threshold, x, pct
```

# Battery Addressable Load Model 2

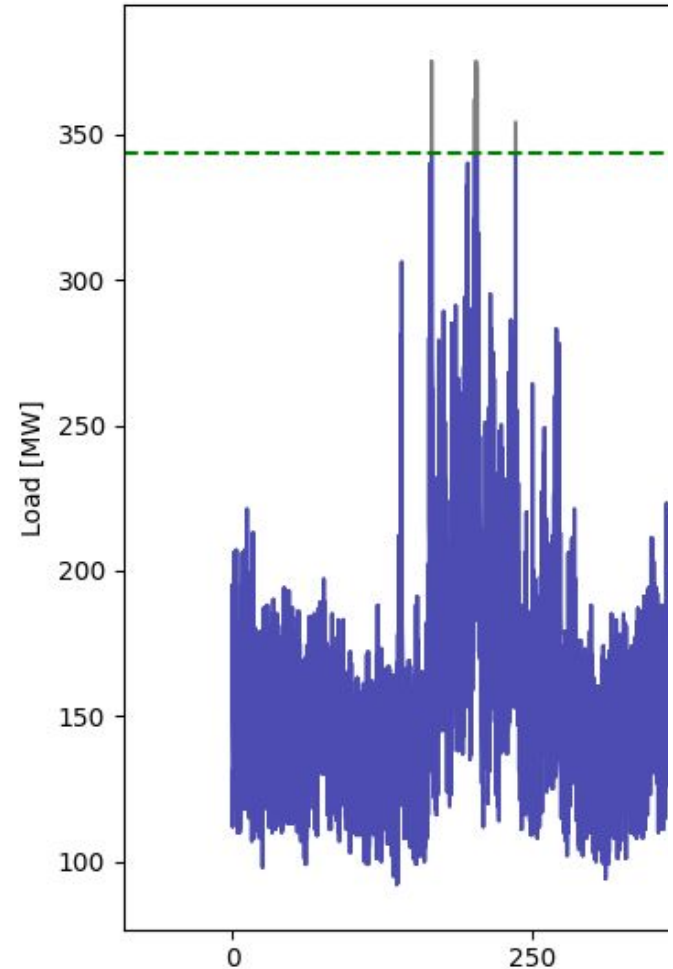


# Battery Addressable Load Model 3



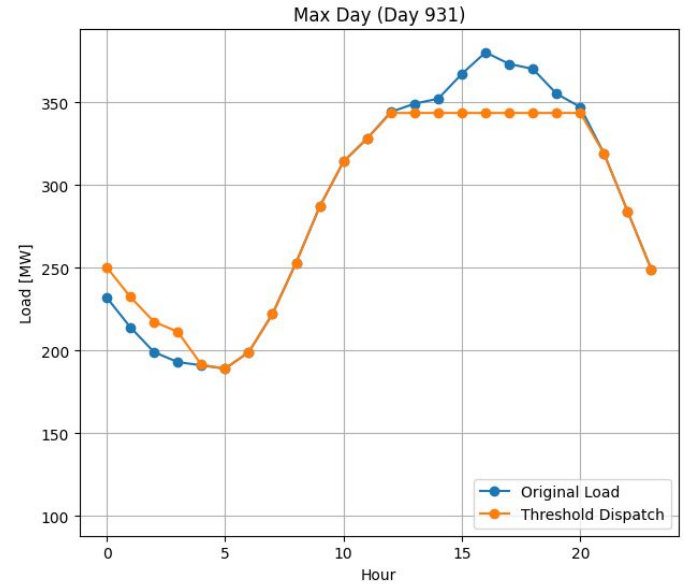
# Threshold Controller Model

```
if hour < 8:
    # Off-peak: charge at rate battery_power/2 (but do not exceed capacity).
    charge_rate = battery_power / 2.0
    charge = min(charge_rate, battery_capacity - SOC)
    SOC += charge
    effective_load = load + charge
    control_action = charge # positive value indicates charging
else:
    # Peak: discharge if load exceeds dispatch threshold.
    if load > dispatch_threshold:
        desired_discharge = load - dispatch_threshold
        discharge = min(desired_discharge, battery_power, SOC)
        SOC -= discharge
        effective_load = load - discharge
        control_action = -discharge # negative value indicates discharging
    else:
        effective_load = load
        control_action = 0.0
```



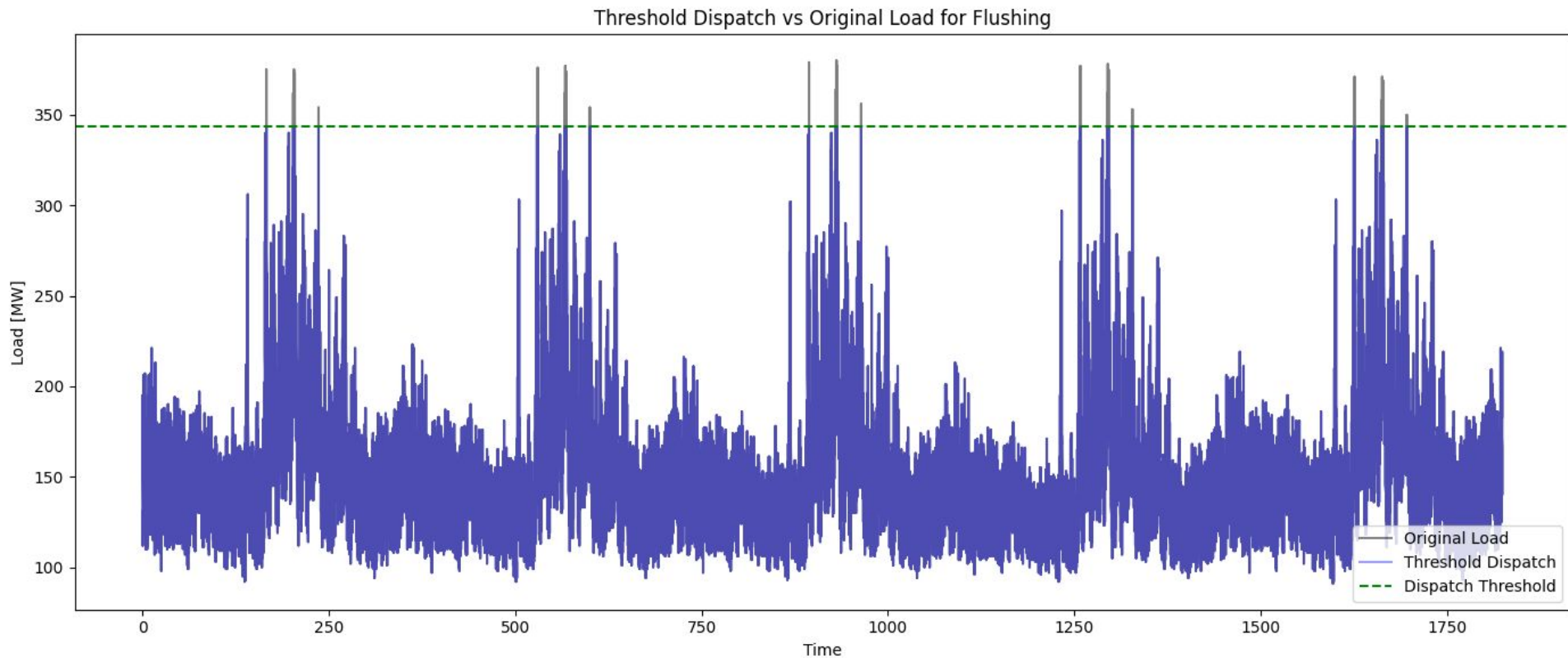
# Failure Modes

- Peak exceeds threshold + battery power
- Energy required exceeds battery capacity

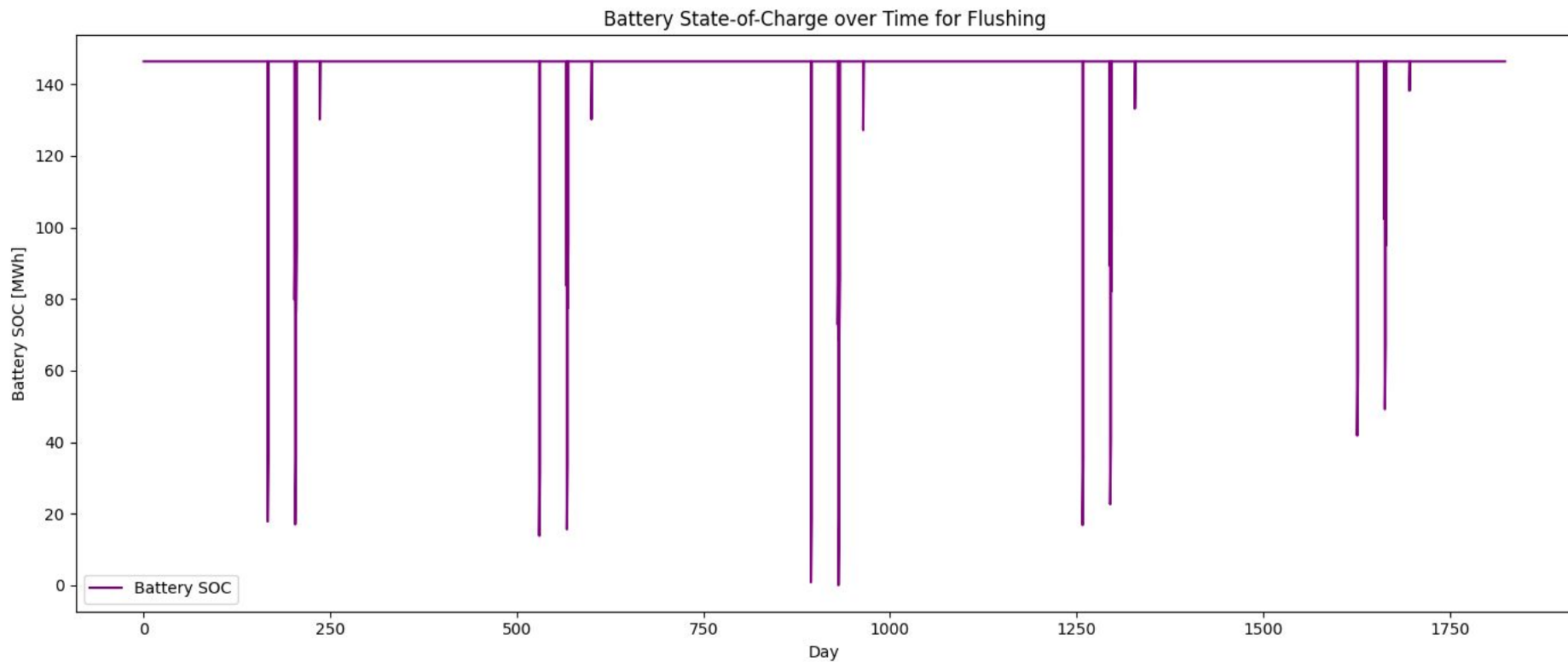




# Visuals 1

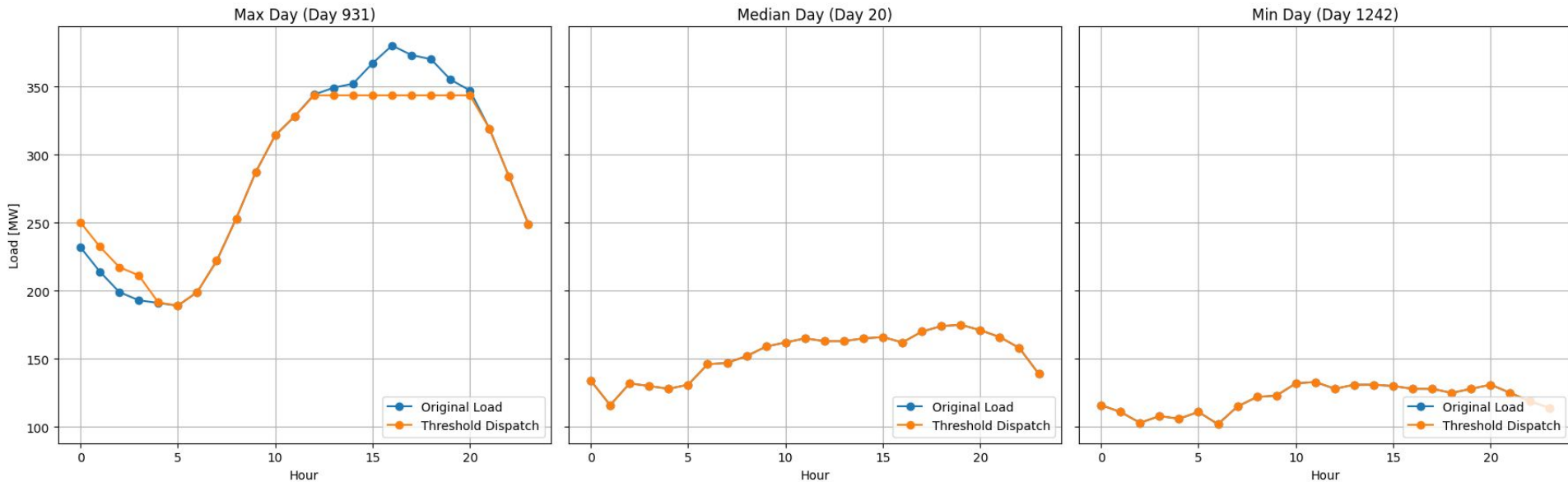


# Visuals 2



# Visuals 3

Comparison of Original and Threshold Dispatch Loads on Extreme Days for Flushing



# What I learned

Cleaning and manipulating time series data can be tricky but also very insightful.

Try lots of things when looking for patterns. Some times visuals are more enlightening than statistics.

I was able to connect what I learn as a mechanical engineer (controllers) to data science!

