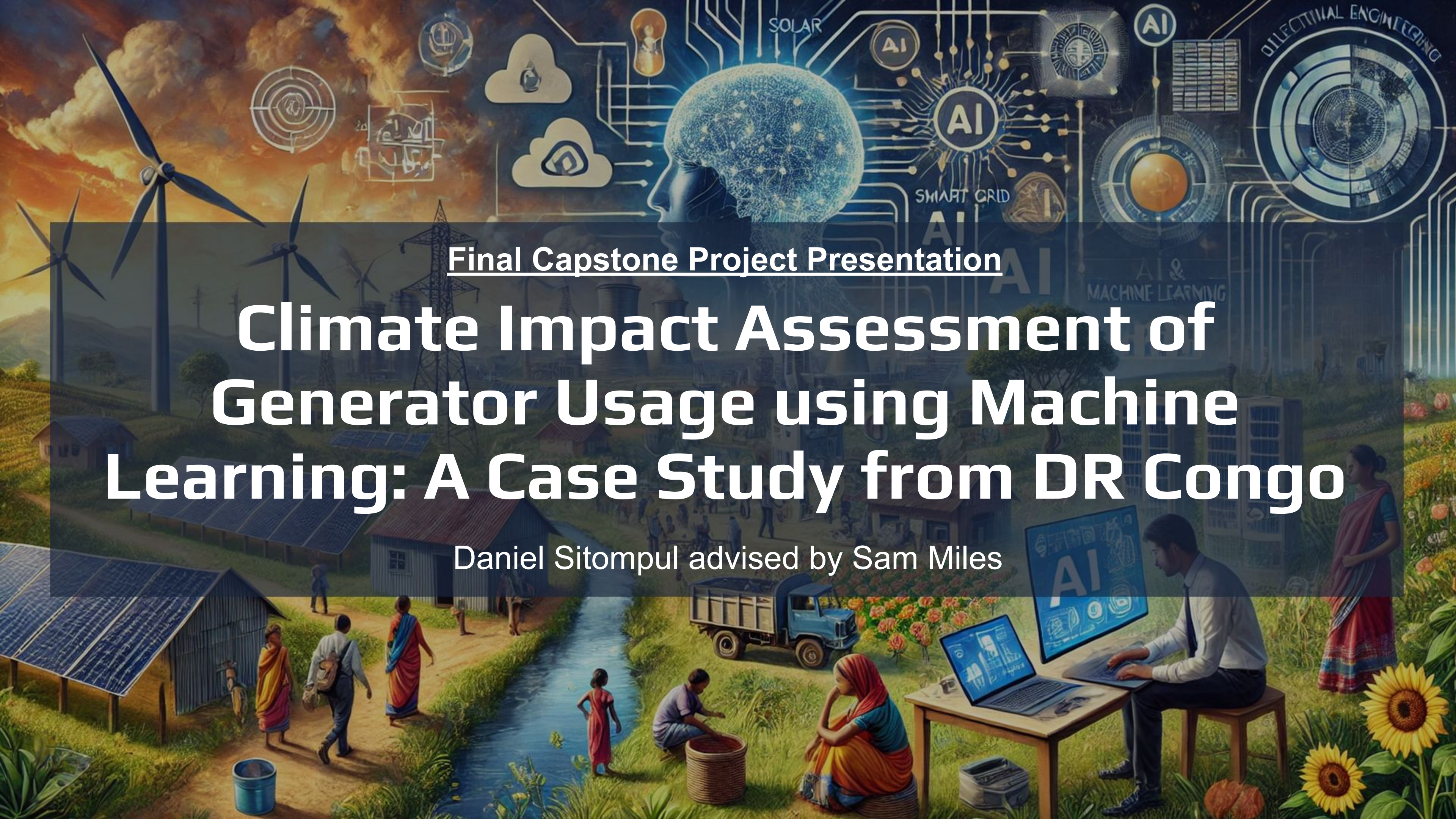


Final Capstone Project Presentation

Climate Impact Assessment of Generator Usage using Machine Learning: A Case Study from DR Congo

Daniel Sitompul advised by Sam Miles

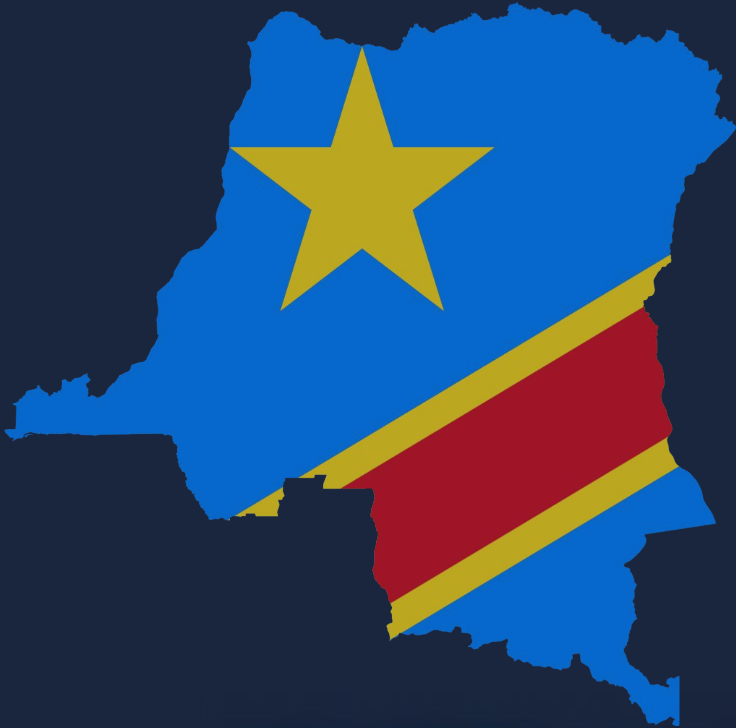
Background

Background

Generator has been mainly the secondary electricity source for health facilities in DR Congo.

Bad grid power quality is the main reason:

- Inconsistent voltage and frequency
- Outages



Background

Generator have **much consistent power (voltage and frequency)**, however the emissions is predicted to produce 3 - 5x higher emission compared to grid power*.

Generator emits different type of **Emissions affecting health**

Figure 1. Generator assessed

Figure 2. Generator emission illustration

*Source:
- A Comparison of Emissions Factors for Electricity Generation, GOV.UK
- Estimation of carbon footprints from diesel generator emissions, IEEE

Background (Past Research)

Wireless sensors linked to climate financing in Nature.com.

nature climate change | LETTERS
PUBLISHED ONLINE: 31 OCTOBER 2016 | DOI: 10.1038/NCLIMATE3141

Wireless sensors linked to climate financing for globally affordable clean cooking

Tara Ramanathan[1], Nithya Ramanathan[1*], Jeevan Mohanty[2], Ibrahim H. Rehman[2], Eric Graham[1] and Veerabhadran Ramanathan[3]

Three billion of the world's poorest people mostly rely on solid biomass for cooking, with major consequences to health[1] and environment[2]. We demonstrate the untapped potential of wireless sensors connected to the 'internet of things' to make clean energy solutions affordable for those at the bottom of the energy pyramid. This breakthrough approach is demonstrated by a 17-month field study with 4,038 households in India. Major findings include: self-reported data on cooking duration have little correlation with actual usage data from sensors; sensor data revealed that the distribution of high and low users varied over time, and the actual mitigation of climate pollution was only 25% of the projected mitigation; climate credits were shown to significantly incentivize the use of cleaner technologies.

Because of poverty and lack of energy access, about 40% of the world's population meet their cooking and heating needs by burning solid biomass in rudimentary stoves[2]. Particles and gases in the smoke from the stoves are major contributors to indoor and outdoor air pollution[3,4], as well as regional and global climate change[5]. The particles emitted by biomass stoves consist mainly of black carbon (BC) and organic carbon (OC)[6], and mix with particles from other sources to form ambient air pollution. Exposure to these particles indoors (mostly in homes) is responsible for 3.5 million deaths annually[1]. There is an environmental impact as well. BC is a strong absorber of solar radiation and hence a climate warming agent[5]. OC consists of particles that both absorb and reflect solar radiation and has a net cooling effect[4]. Other pollutant gases in the smoke form the greenhouse gas ozone. Aside from OC, all of these pollutants lead to net warming[3–5,7,8] and are referred to as short-lived climate pollutants (SLCPs)[8], since their lifetimes (days for BC) are much shorter compared with the century or longer lifetime of CO_2 in the atmosphere. Harvesting of non-renewable biomass as a cooking fuel releases about one billion tonnes of CO_2 each year[3]. Globally, residential combustion of solid biomass for cooking contributes about 40% of BC emissions[9]; in rural India, where the present study was conducted, biomass cooking contributes as much as 50% (ref. 6).

Gas and induction stoves[2,3] are the obvious alternatives to biomass stoves, but the fuel costs[10] are prohibitive given the daily wages of the poorest three billion people[10]. Improved biomass cookstoves (ICS)[2], which still burn locally available biomass, are designed to reduce harmful emissions through more efficient fuel combustion[11–13]. Amongst these, forced-draft ICS (ICS_FD) significantly reduce emissions of CO_2, SLCPs and other particles by increasing the thermal efficiency of combustion and through near-complete combustion. However, at a capital cost of about US$70 (Methods), ICS_FD are out of reach for most of the poorest three billion[10]. Therefore, ICS_FD have typically reached homes by way of project developers at a subsidized cost. Existing carbon markets[14,15] provide credits for reductions in CO_2 to project developers who distribute or sell ICS, rather than rewarding the individuals who use ICS. Indeed, traditional verification methods do not require objective data to quantify individual usage[15]. With one exception, these markets do not permit credits for reductions of SLCPs through ICS[14], and therefore miss opportunities to incentivize adoption of ICS that mitigate both CO_2 and SLCPs. In spite of numerous national and international efforts[2,14], three billion people still rely on rudimentary, polluting stoves.

Affordability of cleaner stoves is one of the major barriers addressed in this study through a breakthrough approach, hereafter referred to as SCF for sensor-enabled climate financing, described below and further detailed in the Methods and Supplementary Methods A–H. SCF differs from traditional approaches to rural cookstove interventions in the following ways: data collected from wireless sensors are used to measure and verify daily cooking duration in each household in near real time; sensor data are converted into climate credits to pay each woman directly for her role in climate change mitigation. Rewarding users is at the heart of the proposed model and to date, we know of no other study

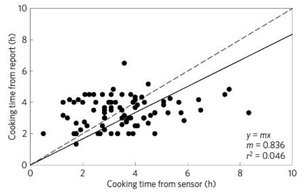


Figure 1 | Comparison of cooking duration from self-reported and sensor-reported data. Sensors were attached to traditional mud stoves, with sensors moved every 24 h to a different house in Uttar Pradesh (data collected during a previous study not described here). Eighty-eight 24-h samples were successfully collected during the six-month period. Cooking time was calculated from sensor data and compared with cooking time reported from surveys. The dashed line is the 1:1 correspondence; the solid line is the linear regression forced through zero (equation parameters inset).

Research Question

Research Question

- With what accuracy, precision and recall can machine learning detect generator usage from voltage and frequency data at monitored health facilities?

- How do generator emissions in Ch Cb Ndosho facility contribute to environmental and public health impacts?

Methodology

Methodology

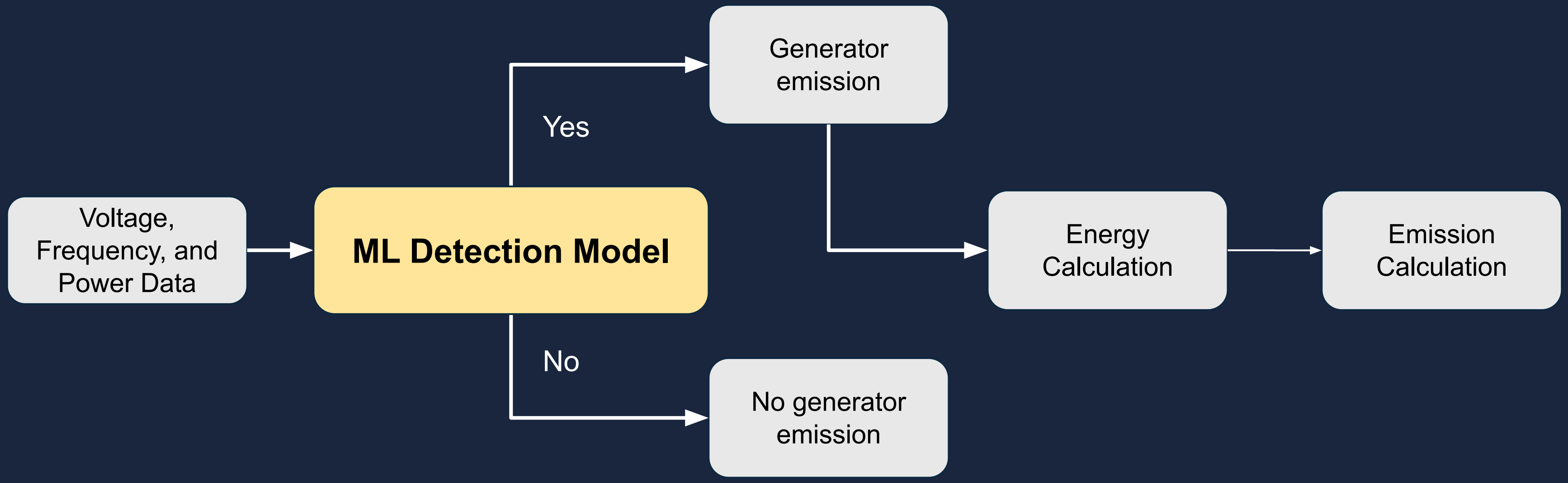


Figure 3. Methodology flowchart

Methodology

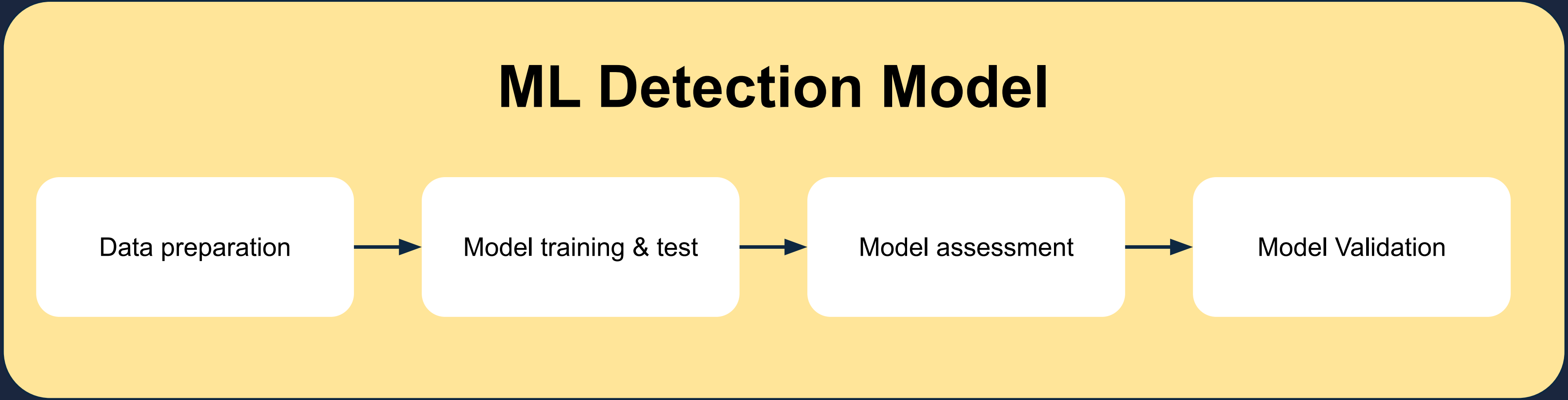


Figure 4. ML detection model flowchart

Data Preparation (volt & freq)

Data Source: Grafana Data Watch Dashboard

Period: 28th May 2022 - *present*

Facility: Ch Cb Bethesda Ndosho

Sensor Location:

- laboratory
- clinic

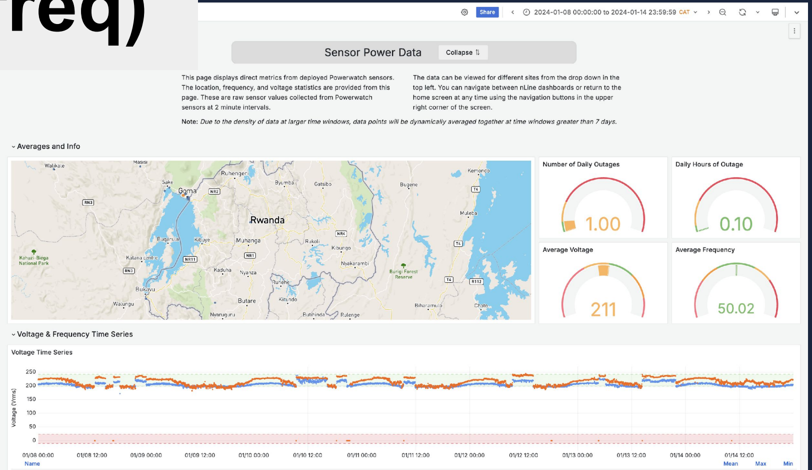


Figure 5 (a). Grafana Dashboard Interface

Figure 5 (b). Voltage and Sensor

Data Preparation (Power)

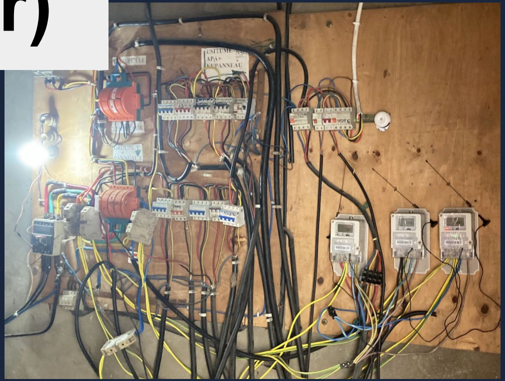


Figure 6 (a). Power sensors

Data Source: Grafana Data Watch Dashboard

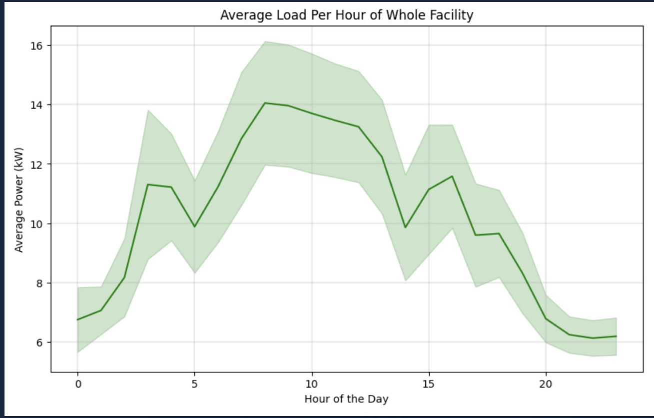
Period: 28th May 2022 - *present*

Facility: Ch Cb Bethesda Ndosho

Sensor Location:

- laboratory
- clinic

Figure 6 (a). Average load per hour



Model Training

Supervised ML by assigning label on the Generator_ON field

- FALSE: Generator turned OFF
- TRUE: Generator turned ON

Training Data: 2 months of data

- 1 Feb 2023 – 28 Feb 2023
- 12 Aug 2024 - 09 Sep 2024

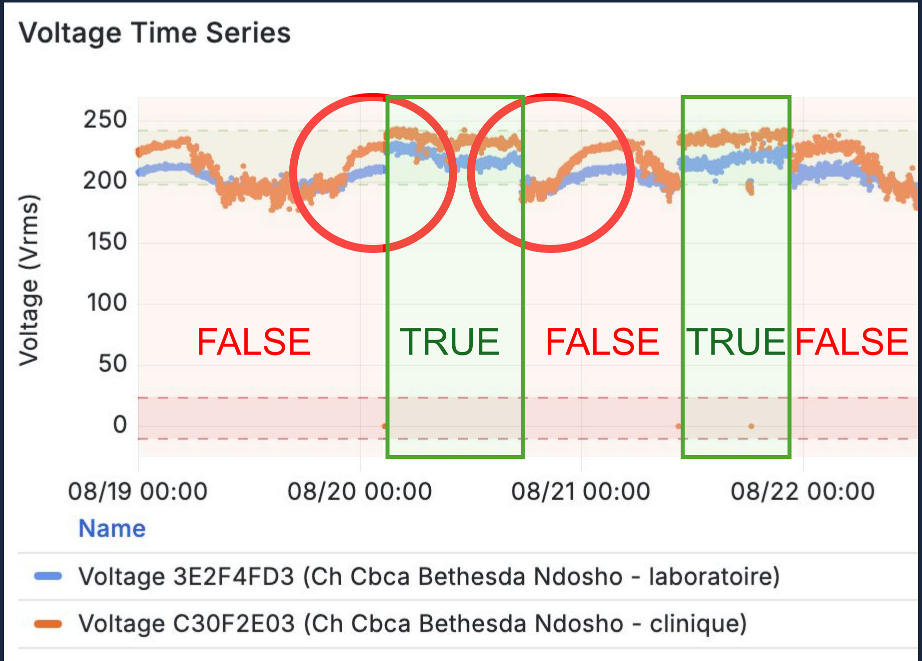


Figure 7. Illustration of label assignment

Data preparation → **Model training & test** | Model assessment | Model Validation

ML Model

Doing feature engineering and applying the data to different models

- **Baseline Model**
- **Mean of Voltage (V) and Frequency (f) as Threshold Model**
  - Logistic Regression
  - Random Forest
  - XGBoost
- **Voltage & frequency mean combined with Time Series Model**
  - Logistic Regression
  - Random Forest
  - XGBoost

Data preparation → **Model training & test** | Model assessment | Model Validation

Assessing the Model

Confusion Matrix:

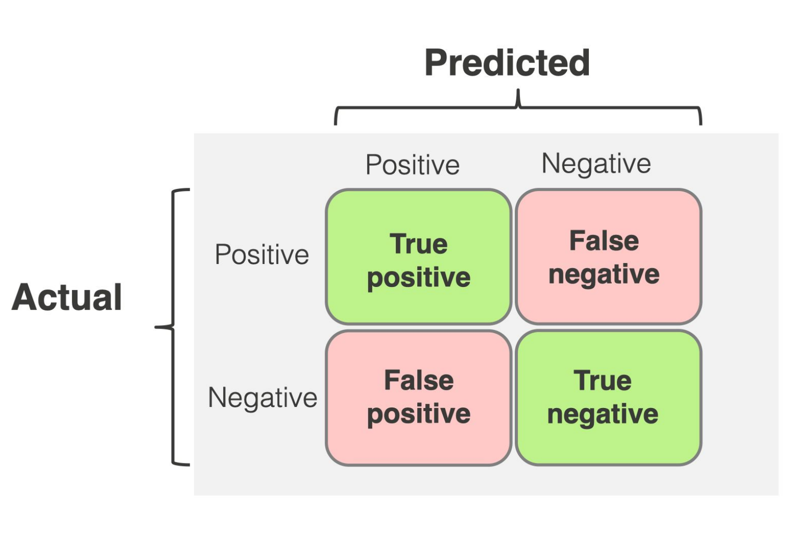


Figure 8. Confusion Matrix

- **Accuracy:** $$\frac{TP + TN}{TP + TN + FP + FN}$$
- **Recall:** $$\frac{TP}{TP + FP}$$
- **Precision:** $$\frac{TP}{TP + FN}$$

Choosing the best model with highest Accuracy, Recall, Precision

Data preparation → Model training & test → **Model assessment** Model Validation

Model Validation

Comparing the model with 1 month (June 2023) actual logged usage

Table 1. Model validation to logged usage

Week (Date Period)	Actual Logged (hours)	ML Prediction (hours)
1 (1st - 7th June 2022)	31	?
2 (8th - 14th June 2022)	19	?
3 (15th - 21st June 2022)	21	?
4 (22nd - 28th June 2022)	18	?
5 (29th - 30th June 2022)	3	?
Total Month of June	**92**	**?**

$$\textbf{\% difference} = \frac{\Sigma\textbf{ML Prediction}}{\Sigma\textbf{Actual logged}} - 1$$

Data preparation → Model training & test → Model assessment → **Model Validation**

Methodology

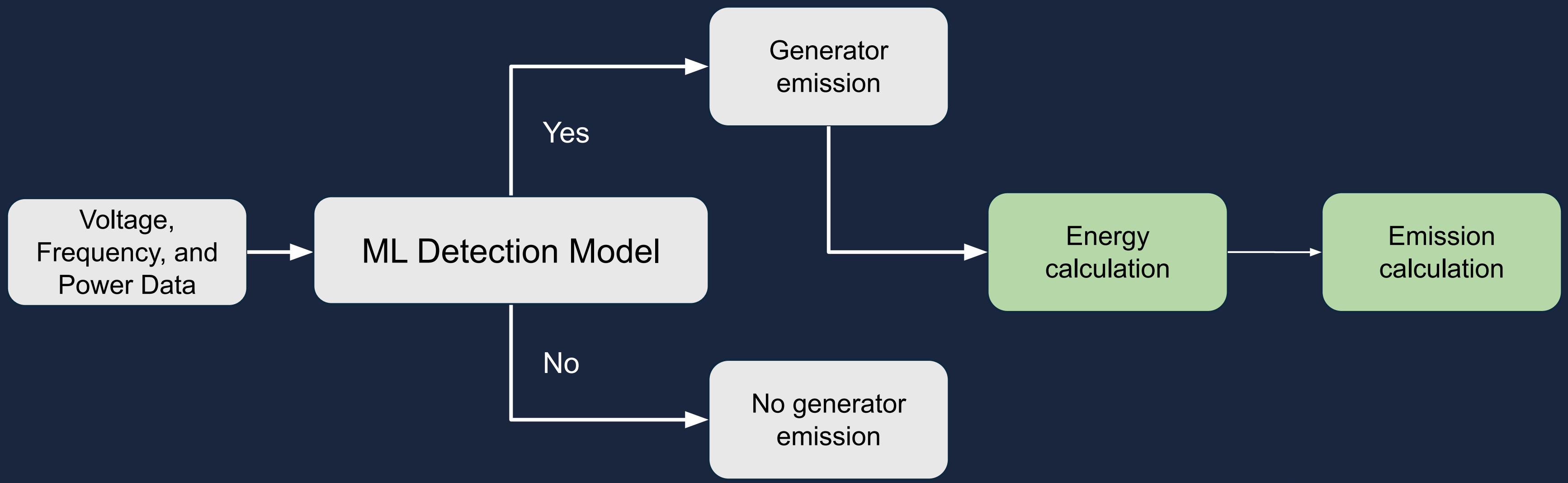


Figure 3. Methodology flowchart

Energy Calculation

Calculating Total Energy (**T**: Total energy consumption in kWh):

Hourly energy by using the minutes of usage at each hours and Average usage number.

$$T_{\text{total}} = \sum_{i=1}^{n} \left(\frac{M_i}{60} \times P_{avg,i} \right)$$

where:

- n is the total number of hours analyzed,
- M_i is the minutes of usage in hour i,
- $P_{avg,i}$ is the average power load in hour i.

Emission Calculation

Total Emissions = Total Energy × Emission Factor

Table 2. Gaseous emission factors for emission calculations

Table 3.4-1. GASEOUS EMISSION FACTORS FOR LARGE STATIONARY DIESEL AND ALL STATIONARY DUAL-FUEL ENGINES[a]

Pollutant	Diesel Fuel (SCC 2-02-004-01)			Dual Fuel[b] (SCC 2-02-004-02)		
	Emission Factor (lb/hp-hr) (power output)	Emission Factor (lb/MMBtu) (fuel input)	EMISSION FACTOR RATING	Emission Factor (lb/hp-hr) (power output)	Emission Factor (lb/MMBtu) (fuel input)	EMISSION FACTOR RATING
NO_x						
Uncontrolled	0.024	3.2	B	0.018	2.7	D
Controlled	0.013[c]	1.9[c]	B	ND	ND	NA
CO	5.5 E-03	0.85	C	7.5 E-03	1.16	D
SO_x[d]	8.09 E-03S_1	1.01S_1	B	4.06 E-04S_1 + 9.57 E-03S_2	0.05S_1 + 0.895S_2	B
CO_2[e]	1.16	165	B	0.772	110	B
PM	0.0007[c]	0.1[c]	B	ND	ND	NA
TOC (as CH_4)	7.05 E-04	0.09	C	5.29 E-03	0.8	D
Methane	f	f	E	3.97 E-03	0.6	E
Nonmethane	f	f	E	1.32 E-03	0.2[g]	E

Source: **U.S. Environmental Protection Agency**
https://www3.epa.gov/ttnchie1/ap42/ch03/final/c03s04.pdf

Results

Model Test Summary

Table 3. Model test result summary

No	Model	Feature	Accuracy	Precision	Recall
1.	Baseline	V & Freq	0.8166	0	0
3.	Logistic Regression	Mean Threshold	0.7084	0.3859	0.9988
4.	Random Forest		0.9118	0.9495	0.5481
5.	XG-Boost		0.9664	0.9527	0.8596
6.	Logistic Regression	**Mean & Time-Series**	0.9698	0.9853	0.8481
7.	**Random Forest**		**0.9933**	**0.9969**	**0.9669**
8.	XG-Boost		0.9916	0.9943	0.9594
9.	**XG-Boost (CV tuned)**		**0.9939**	**0.9951**	**0.972**

Result: 2023 Data (5th - 9th April 2023)

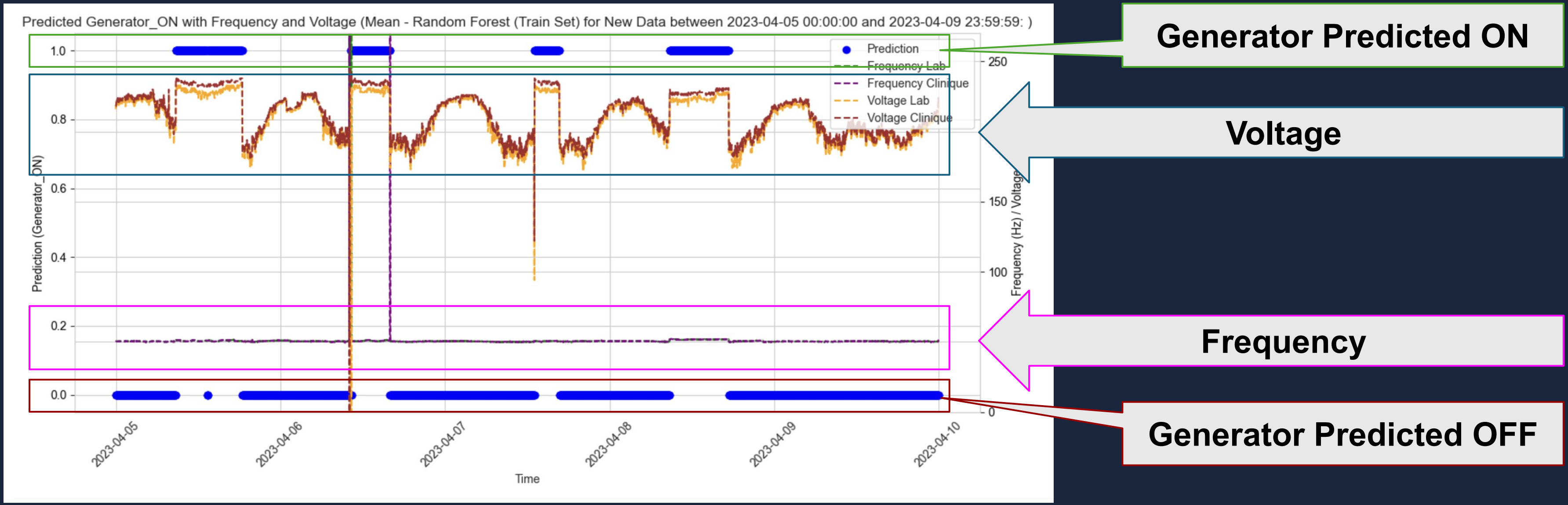


Figure 9. Voltage, frequency, and ML predictions between 5th - 9th April 2023

Result: 2023 Data (Zoom in)

Prediction when lost of sensor data on the Clinique between 16th of July to 2nd of August.

	Date	Count	Minutes	Hours
0	2023-07-16	59	118	1.966667
1	2023-07-17	97	194	3.233333
2	2023-07-18	300	600	10.000000
3	2023-07-19	248	496	8.266667
4	2023-07-20	251	502	8.366667
5	2023-07-21	279	558	9.300000
6	2023-07-22	165	330	5.500000
7	2023-07-24	159	318	5.300000
8	2023-07-25	249	498	8.300000
9	2023-07-26	246	492	8.200000

Figure 10. Detection count translated to minutes / hours

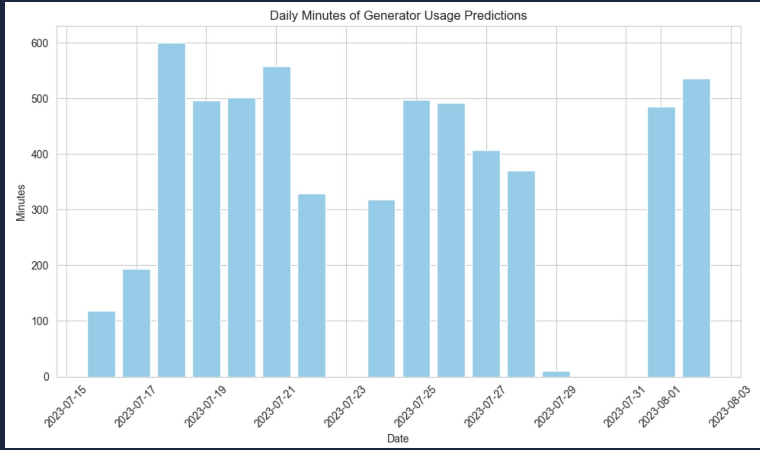


Figure 11. Bar chart on daily usage (minutes)

```
##### PREDICTION RESULT #####
Predicted Minutes: 5916 minutes, or 98.60 hours within 432.00 hours
```

Picture 12. Prediction result within a given time period

Validation with Logged Data

Validation: June 2022 Data

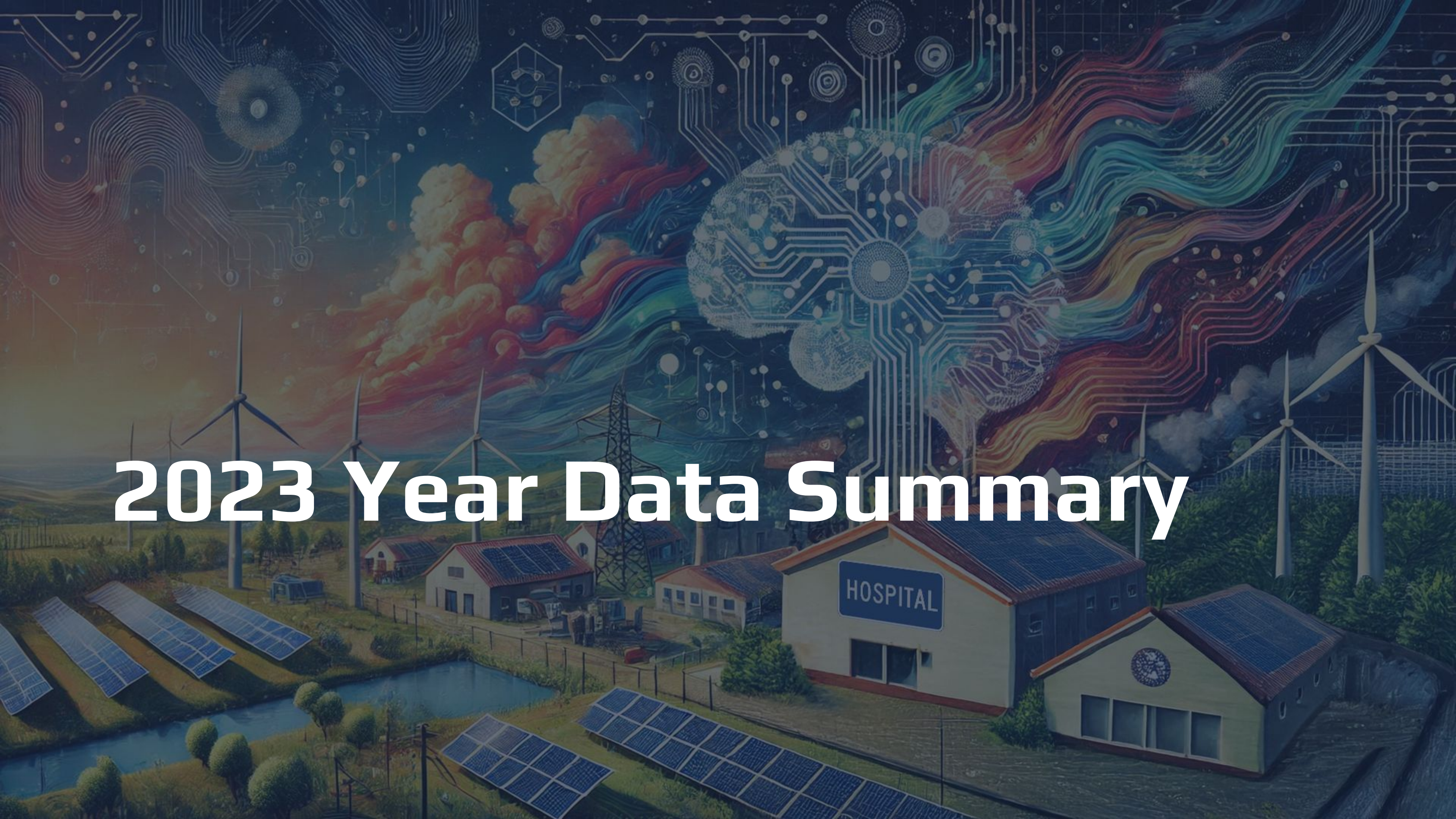
Table 4. Random forest validation result (June 2022)

Week (Date Period)	Actual Logged (hours)	ML RF Prediction (hours)
1 (1st - 7th June 2022)	31	32.8
2 (8th - 14th June 2022)	19	21.3
3 (15th - 21st June 2022)	21	22.4
4 (22nd - 28th June 2022)	18	15.7
5 (29th - 30th June 2022)	3	0
Total Month of June	**92**	**92.2**

Difference : 0.217%.

This difference of 0.2 hours, indicating a highly accurate model.

2023 Year Data Summary



Calculating Total Energy

$$T_{\text{total}} = \sum_{i=1}^{n} \left(\boxed{\frac{M_i}{60}} \times \boxed{P_{avg,i}} \right)$$

where:

- n is the total number of hours analyzed,
- M_i is the minutes of usage in hour i,
- $P_{avg,i}$ is the average power load in hour i.

X

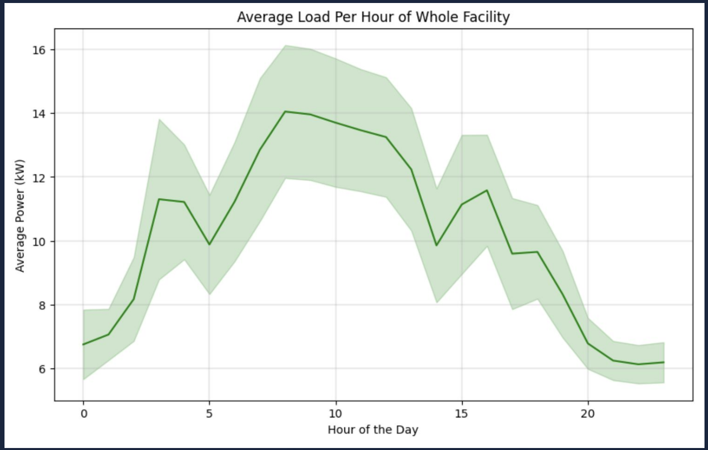


Figure 13. Prediction result within a given time of a day

Figure 14. Generator average hourly load

2023 Year Data Summary

Table 5. Emission calculations result for 2023

Metric	Total	TCO2e
Time (minutes)	113,200	-
Energy (kWh)	22,295	-
Emission		
CO2	15.769 tones	15.769
NOx	326.247 kg	97.222
CO	74.765 kg	0.075
SOx	109.972 kg	0
PM	9.515 kg	0

Low Estimate:
113.066 TCO_2e × $8/tonne = **$904.53**

Medium Estimate:
113.066 TCO_2e × $30/tonne = **$3,391.98**

EU ETS Estimate:
113.066 TCO_2e × $70/tonne = **$7,914.62**

Offsetting **113.066 TCO_2e** would cost between **$904.53 and $7,914.62** in the voluntary carbon market.

Conclusion

Conclusion

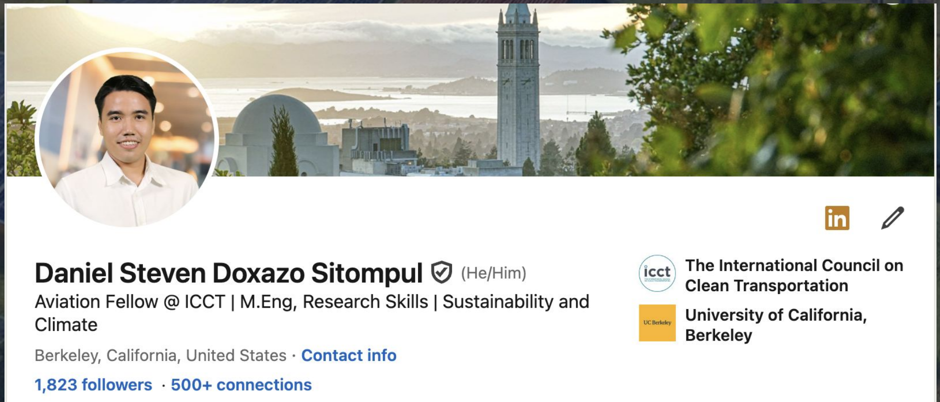
- **Machine learning** has a **potential to predict generator usage**, this will help on **understanding emissions** generated.
- **Our model** show an **accurate prediction** with more than **99% accuracy, 99% precision, and 96% recall** using Random Forest and XGBoost.
- **Climate financing** from generators using **machine learning** become a potential future compared to controversial cookstoves.

Next Steps

- Writing a paper (currently in draft)
- Explore other metering methodology
- Applying the model to other facilities

THANK YOU!

More of my projects:
github.com/Danielstevends/



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Appendix

1. Baseline Model - Result

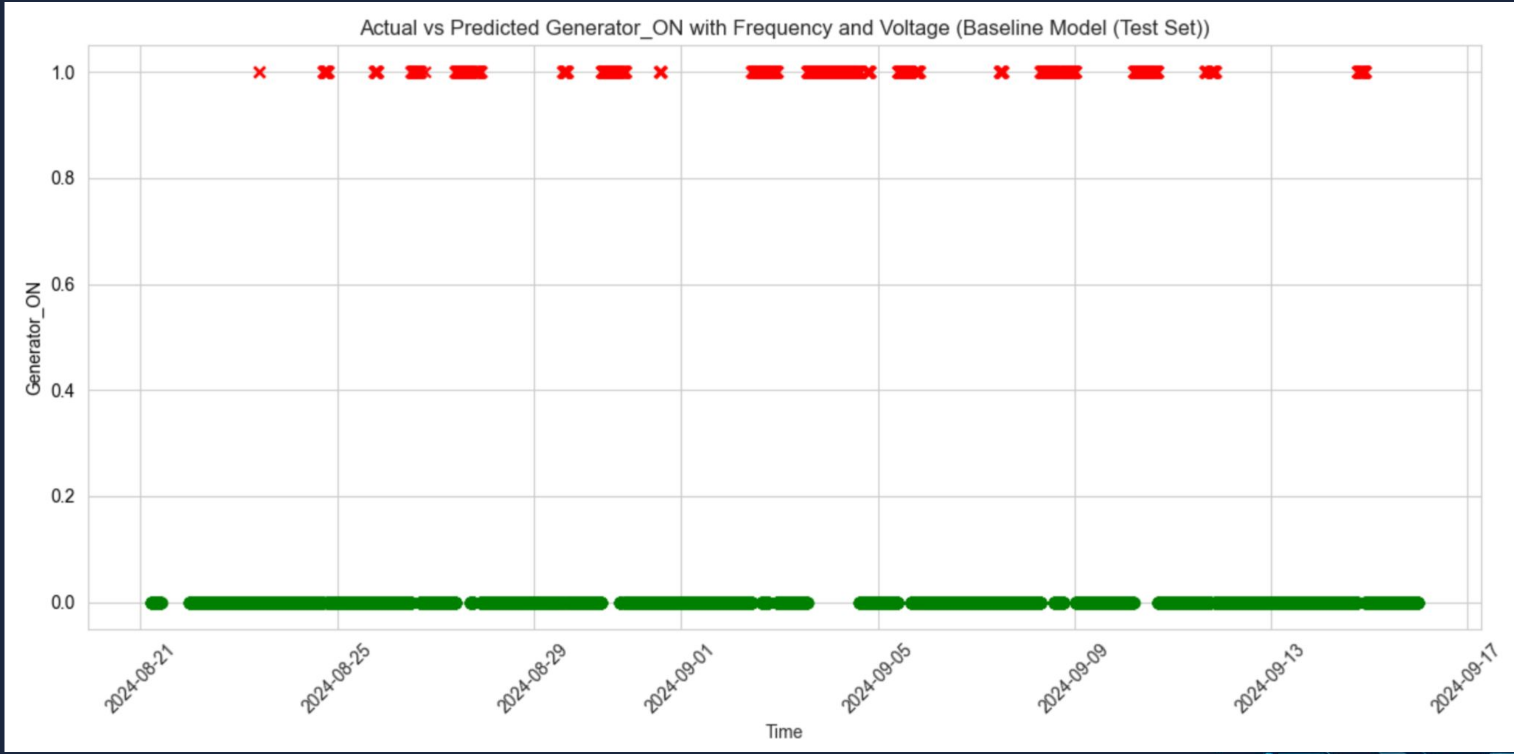
- Using the most common value in the training dataset.
- Most common value: FALSE
- Train Result:

```
Accuracy of model: 0.8528439153439153
Confusion Matrix:
[[23211     0]
 [ 4005     0]]
Precision of model: 0.0
Recall of model: 0.0
```

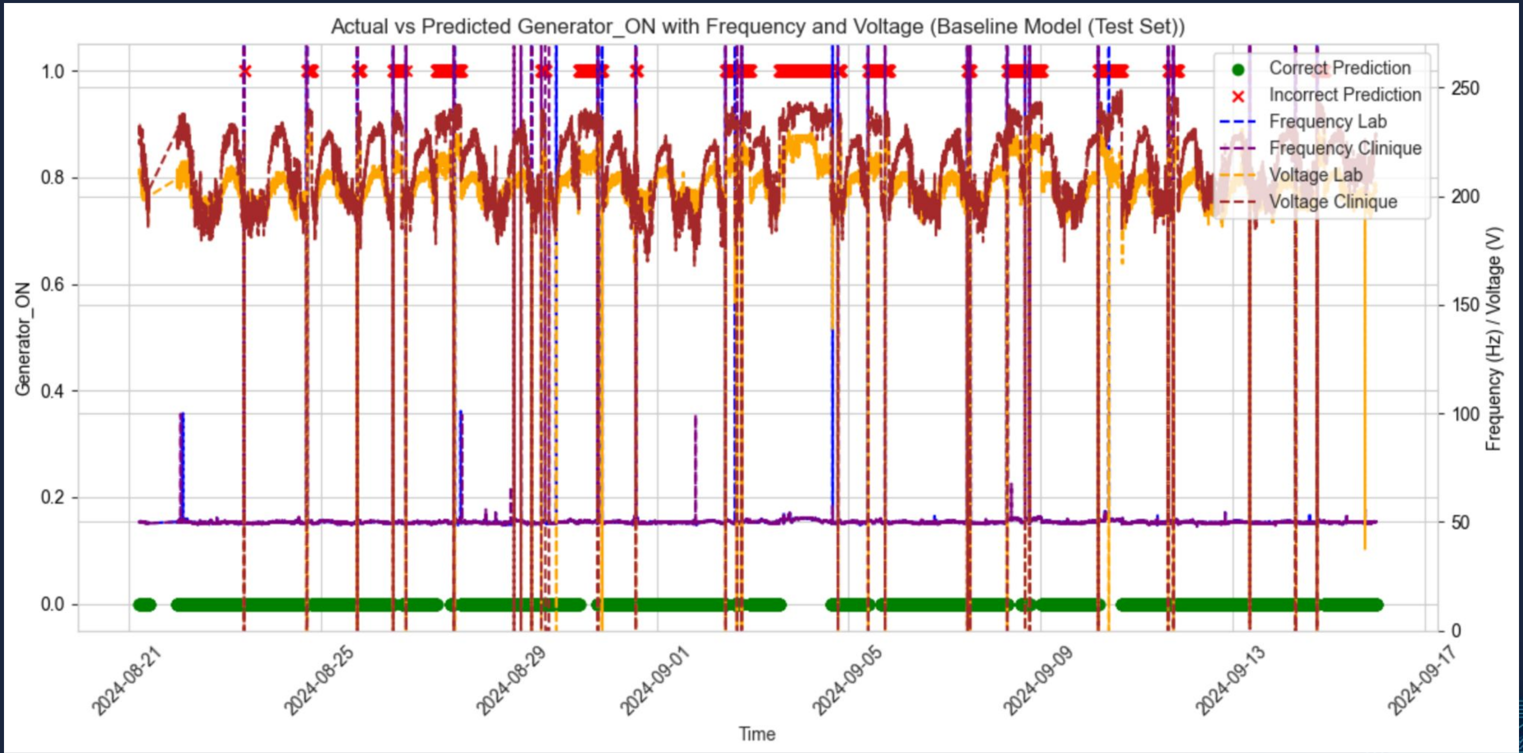
- Test Result:

```
Accuracy of model: 0.8166887125220459
Confusion Matrix:
[[14818     0]
 [ 3326     0]]
Precision of model: 0.0
Recall of model: 0.0
```

1. Baseline Model



1. Baseline Model



2. Mean Model

- Using the mean in the model to create a prediction
  - Taking the mean of frequency and voltage of both facilities as the threshold
  - Custom:
    - True:
    - False:
  - Random Forest & XG Boost: Utilizing the value of 4 new mean based features values.

2.1. Mean Model - Custom

- Train Result:

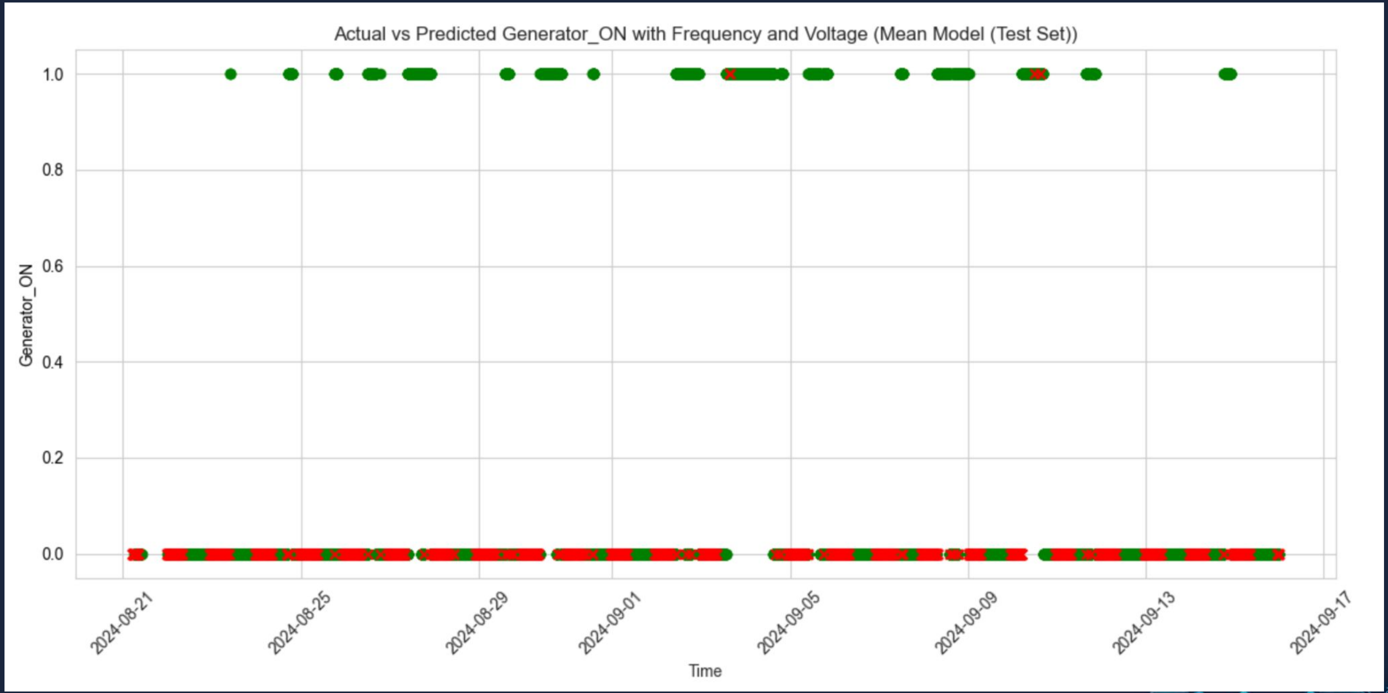
```
Accuracy of model: 0.6511610817166372
Confusion Matrix:
[[13720  9491]
 [    3  4002]]
Precision of model: 0.29659823612243386
Recall of model: 0.9992509363295881
```

- Test Result:

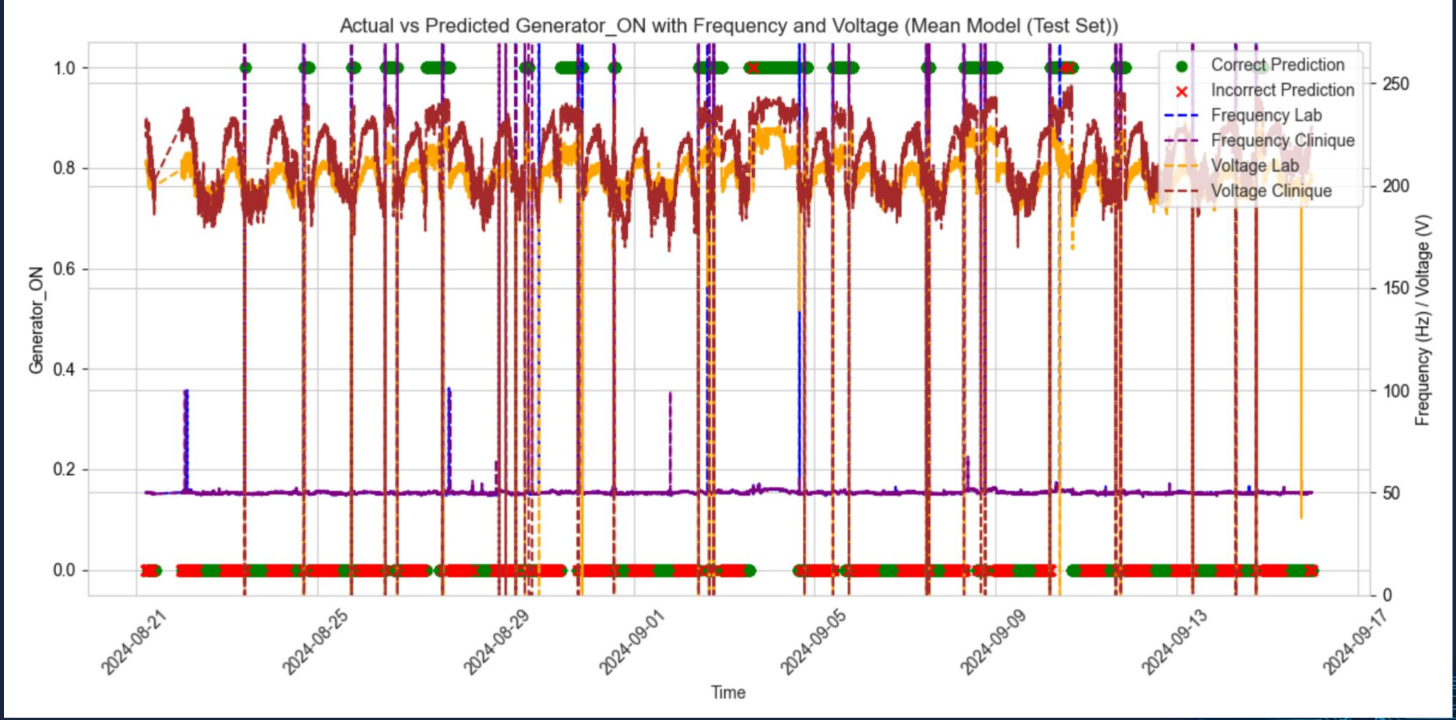
```
Accuracy of model: 0.7084435626102292
Confusion Matrix:
[[9532 5286]
 [   4 3322]]
Precision of model: 0.3859207434944237
Recall of model: 0.9987973541791942
```

Results given by the model have lower accuracy however, the precision and recall is significantly higher compared to the baseline.

2.1. Mean Model - Custom



2.1. Mean Model - Custom



2.2. Mean Model – Logistic Regression

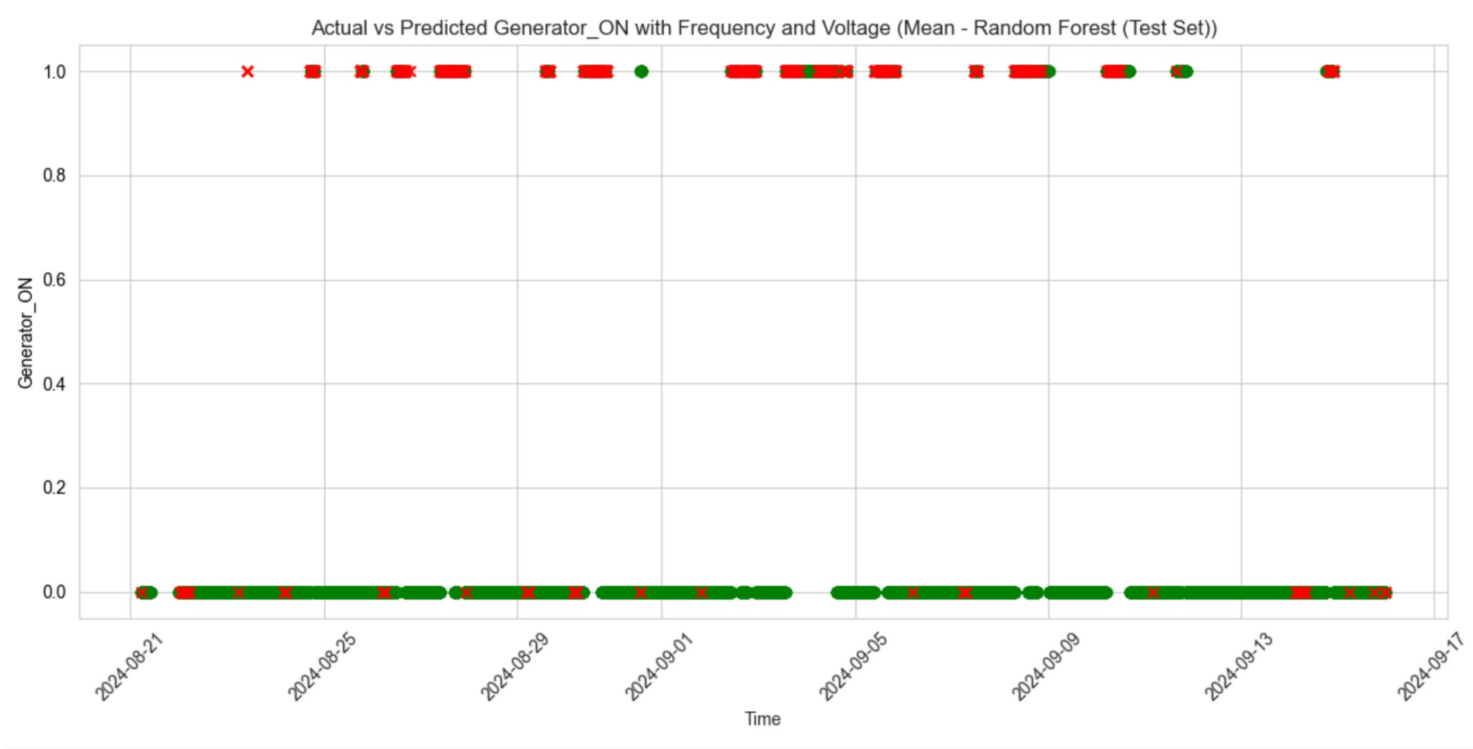
- Train Result:

```
Train Set Evaluation:
Accuracy: 0.8907260435038212
Confusion Matrix:
[[23130    81]
 [ 2893  1112]]
Precision: 0.9321039396479464
Recall: 0.2776529338327091
Train data prediction distribution:
prediction
0    26023
1     1193
Name: count, dtype: int64
```

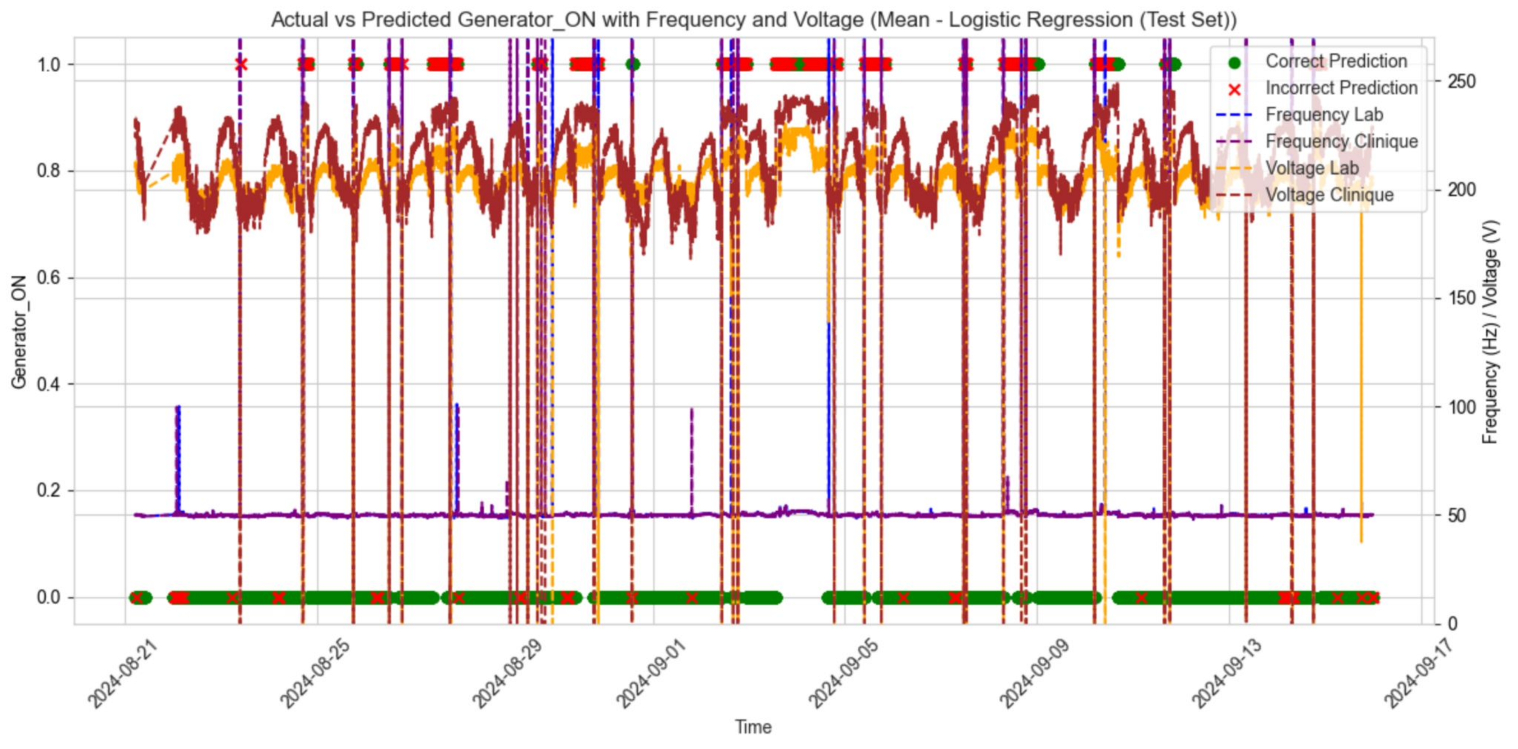
- Test Result:

```
Test Set Evaluation:
Accuracy: 0.9118165784832452
Confusion Matrix:
[[14721    97]
 [ 1503  1823]]
Precision: 0.9494791666666667
Recall: 0.5481058328322309
Test data prediction distribution:
prediction
0    16224
1     1920
Name: count, dtype: int64
```

2.2. Mean Model – Logistic Regression



2.2. Mean Model – Logistic Regression



2.3. Mean Model – Random Forest

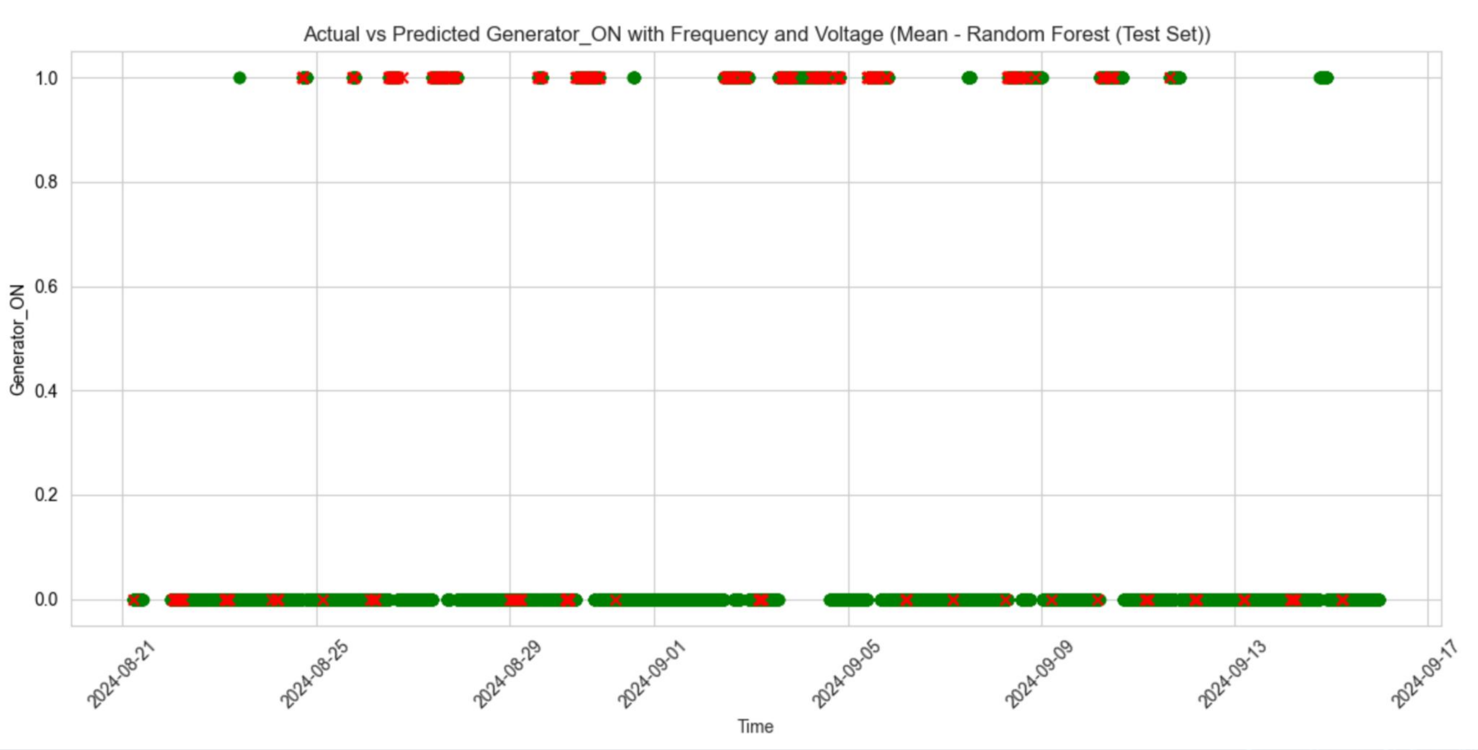
- Train:

```
Train Set Evaluation:
Accuracy: 0.9971340388007055
Confusion Matrix:
[[23189    22]
 [   56  3949]]
Precision: 0.9944598337950139
Recall: 0.9860174781523097
Train data prediction distribution:
prediction
False    23245
True      3971
Name: count, dtype: int64
```

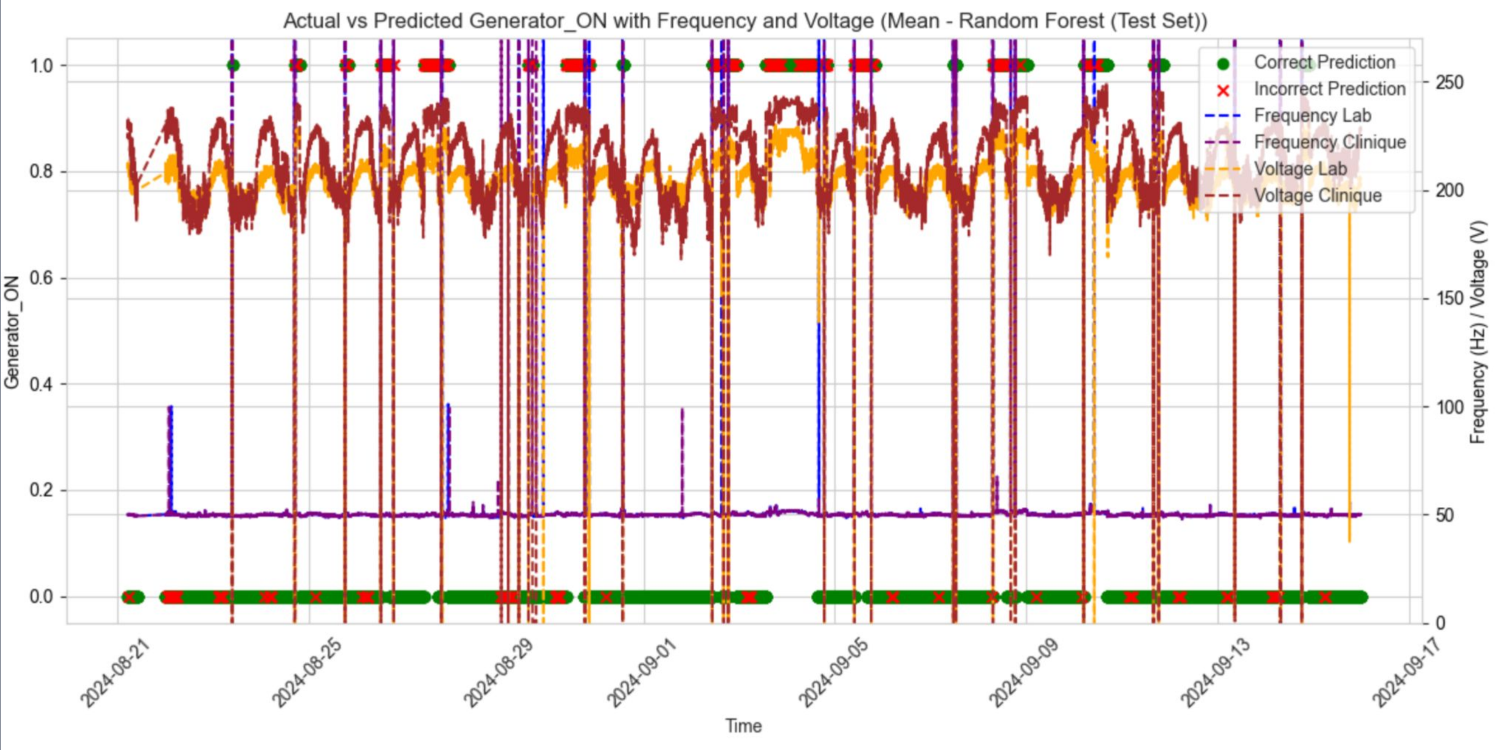
- Test:

```
Test Set Evaluation:
Accuracy: 0.9660493827160493
Confusion Matrix:
[[14687   131]
 [  485  2841]]
Precision: 0.9559219380888291
Recall: 0.8541791942273
Test data prediction distribution:
prediction
False    15172
True      2972
Name: count, dtype: int64
```

2.3. Mean Model – Random Forest



2.3. Mean Model – Random Forest



2.3. Mean Model – XG-Boost

Best parameters: {'colsample_bytree': 0.6, 'gamma': 0, 'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 300, 'reg_alpha': 0, 'reg_lambda': 1, 'subsample': 1.0}

- Train:

```
Train Set Evaluation (XGBoost):
Accuracy: 0.9963624338624338
Confusion Matrix:
[[23138    73]
 [   26  3979]]
Precision: 0.9819842053307009
Recall: 0.9935081148564294
Train data prediction distribution (XGBoost):
prediction
0    23164
1     4052
Name: count, dtype: int64
```

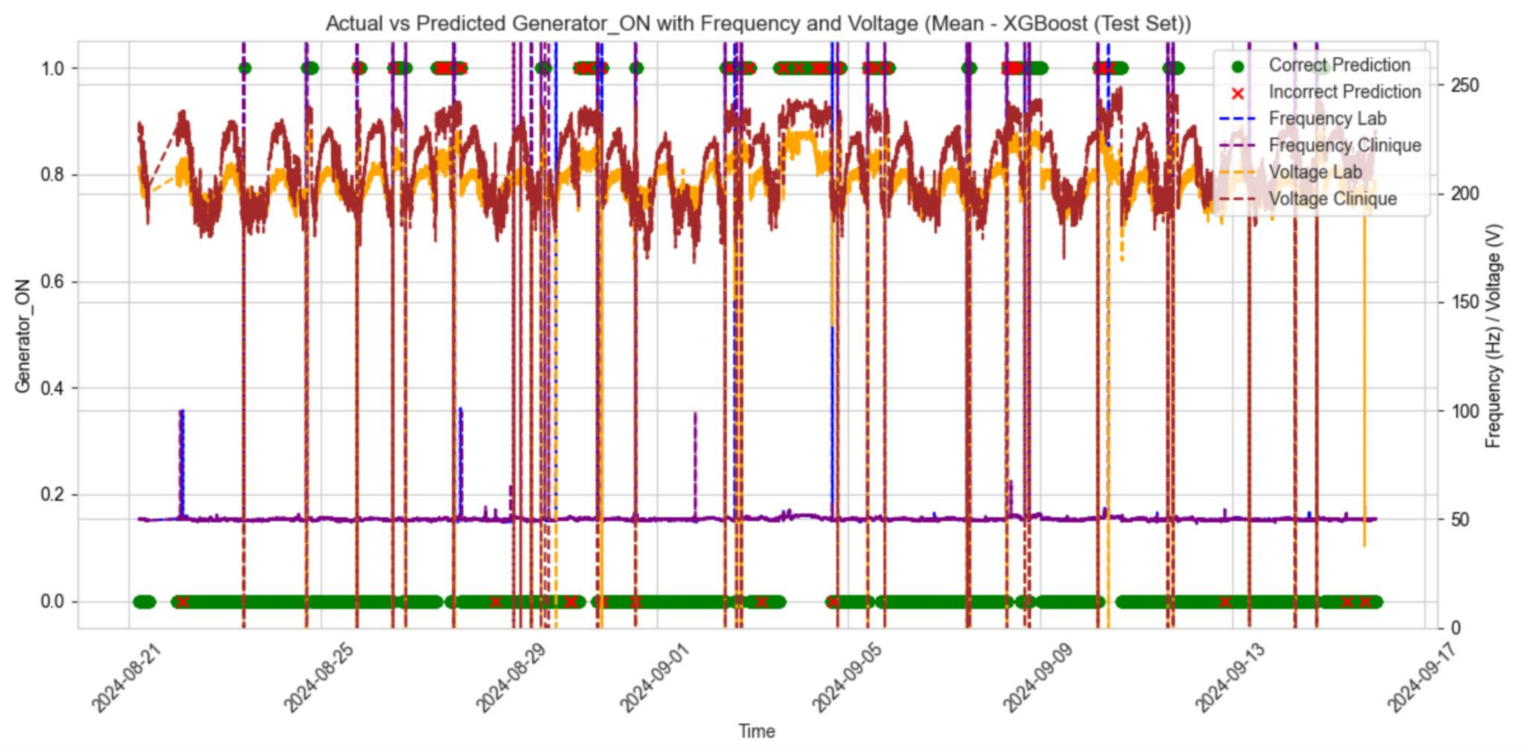
- Test:

```
Test Set Evaluation (XGBoost):
Accuracy: 0.9939925044091711
Confusion Matrix:
[[14802    16]
 [   93  3233]]
Precision: 0.9950754078177901
Recall: 0.9720384846662657
Test data prediction distribution (XGBoost):
prediction
0    14895
1     3249
Name: count, dtype: int64
```

2.3. Mean Model – XG-Boost

```
Classification Report:
              precision    recall  f1-score   support

       False       0.99      1.00      1.00     14818
        True       1.00      0.97      0.98      3326

    accuracy                           0.99     18144
   macro avg       0.99      0.99      0.99     18144
weighted avg       0.99      0.99      0.99     18144

AUC-ROC Score:
0.9994967298957964
Confusion Matrix:
[[14802    16]
 [   93  3233]]
```

2.3. Mean Model – XG-Boost



3. Time Series Model

Creating features related to Time:
- Days of the Week
- Hours of the Day

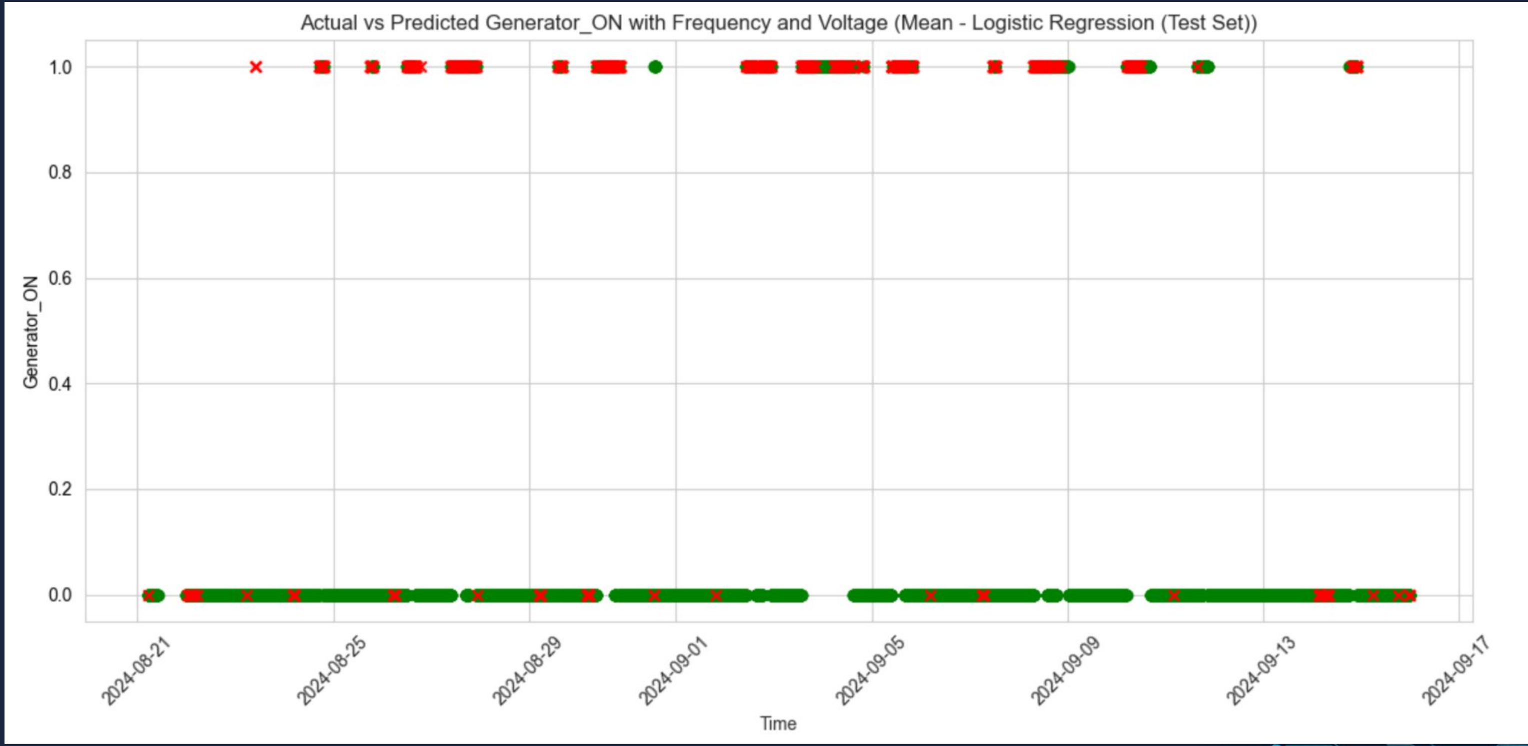
3.1. Time Series - Logistic Regression

```
Train Set Evaluation:
Accuracy: 0.9761537330981775
Confusion Matrix:
[[22955   256]
 [  393  3612]]
Precision: 0.9338159255429163
Recall: 0.90187265917603
Train data prediction distribution:
prediction
False    23348
True      3868
Name: count, dtype: int64
```

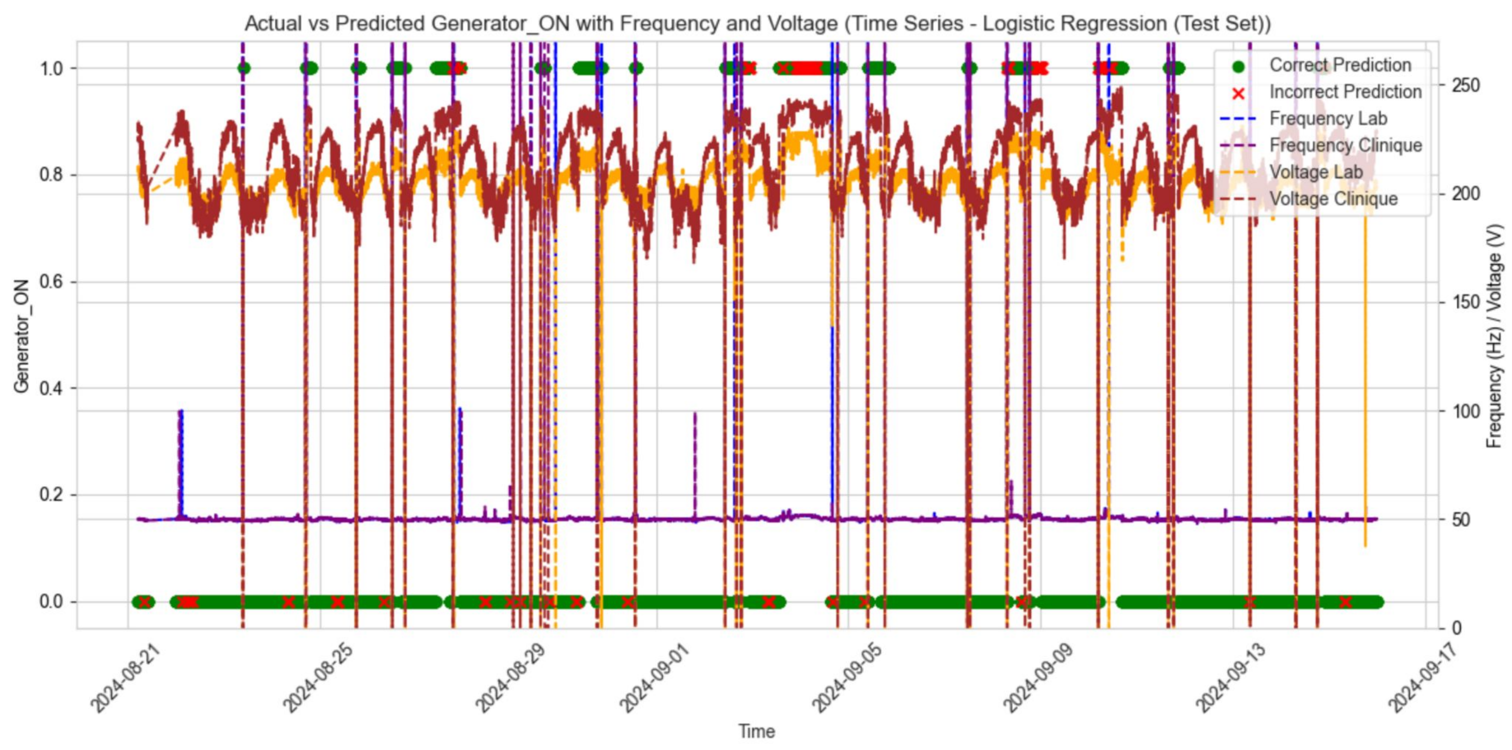
```
Test Set Evaluation:
Accuracy: 0.969852292768959 5
Confusion Matrix:
[[14776    42]
 [  505  2821]]
Precision: 0.9853300733496333
Recall: 0.8481659651232712
Test data prediction distribution:
prediction
False    15281
True      2863
Name: count, dtype: int64
```

```
##### PREDICTION RESULT #####
Actual Minutes: 4005 minutes, or 66.75 hours within 453.60 hours
Predicted Minutes: 3868 minutes, or 64.47 hours within 453.60 hours
Actual Minutes: 3326 minutes, or 55.43 hours within 302.40 hours
Predicted Minutes: 2863 minutes, or 47.72 hours within 302.40 hours
```

3.1. Time Series - Logistic Regression



3.1. Time Series - Logistic Regression



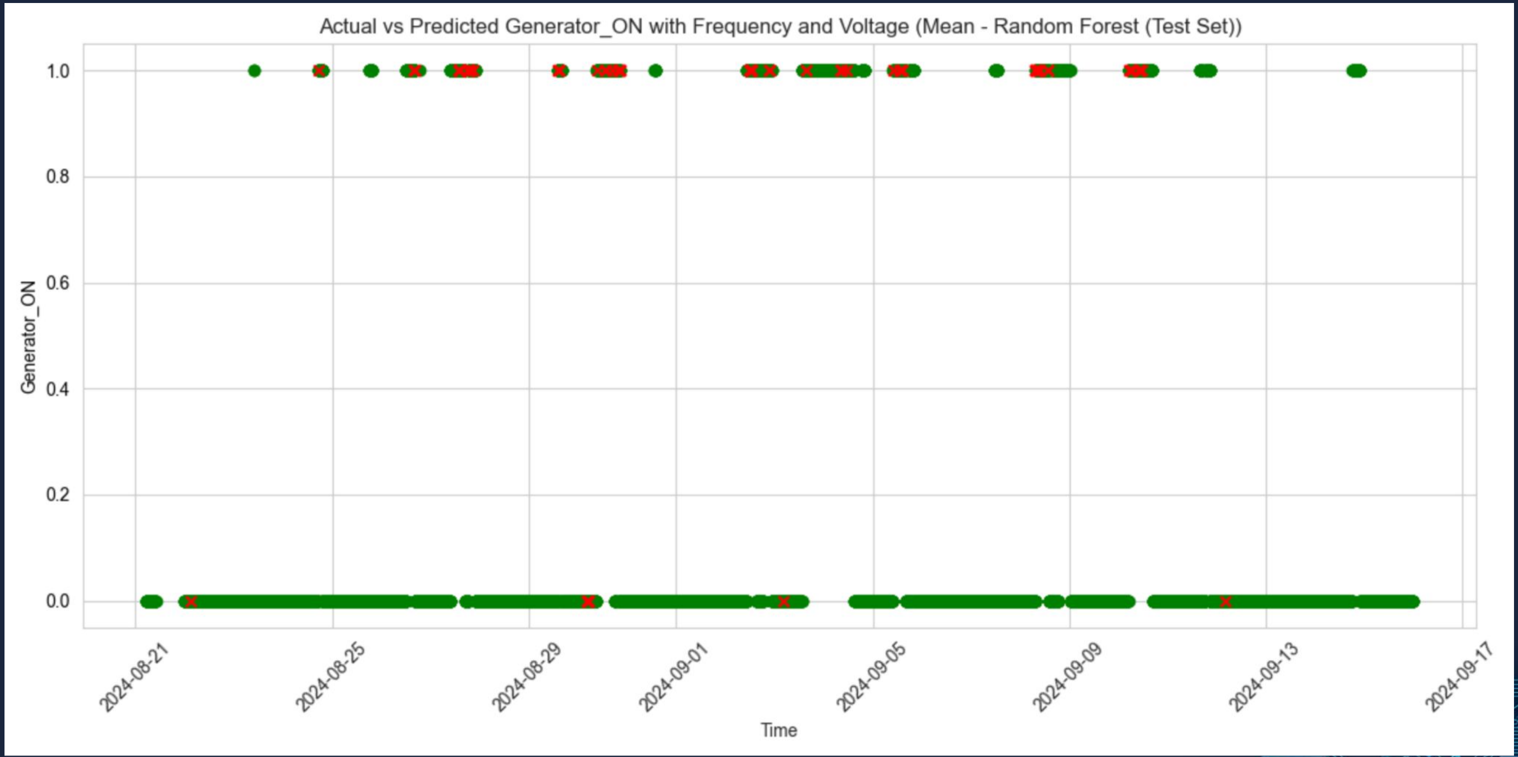
3.2. Time Series - Random Forest

```
Train Set Evaluation:
Accuracy: 1.0
Confusion Matrix:
[[23211     0]
 [    0  4005]]
Precision: 1.0
Recall: 1.0
Train data prediction distribution:
prediction
False    23211
True      4005
Name: count, dtype: int64
```

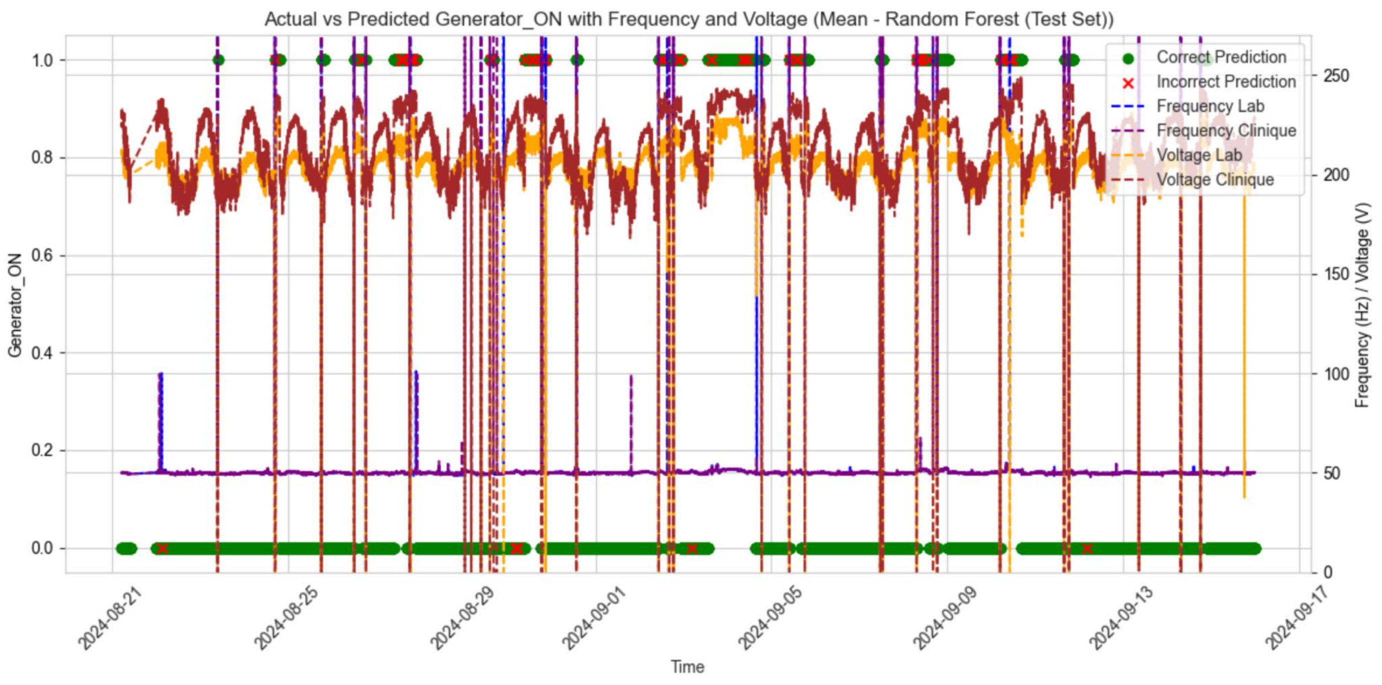
```
Test Set Evaluation:
Accuracy: 0.9933862433862434
Confusion Matrix:
[[14808    10]
 [  110  3216]]
Precision: 0.9969001859888407
Recall: 0.9669272399278412
Test data prediction distribution:
prediction
False    14918
True      3226
Name: count, dtype: int64
```

```
##### PREDICTION RESULT #####
Actual Minutes: 4005 minutes, or 66.75 hours within 453.60 hours
Predicted Minutes: 4005 minutes, or 66.75 hours within 453.60 hours
Actual Minutes: 3326 minutes, or 55.43 hours within 302.40 hours
Predicted Minutes: 3226 minutes, or 53.77 hours within 302.40 hours
```

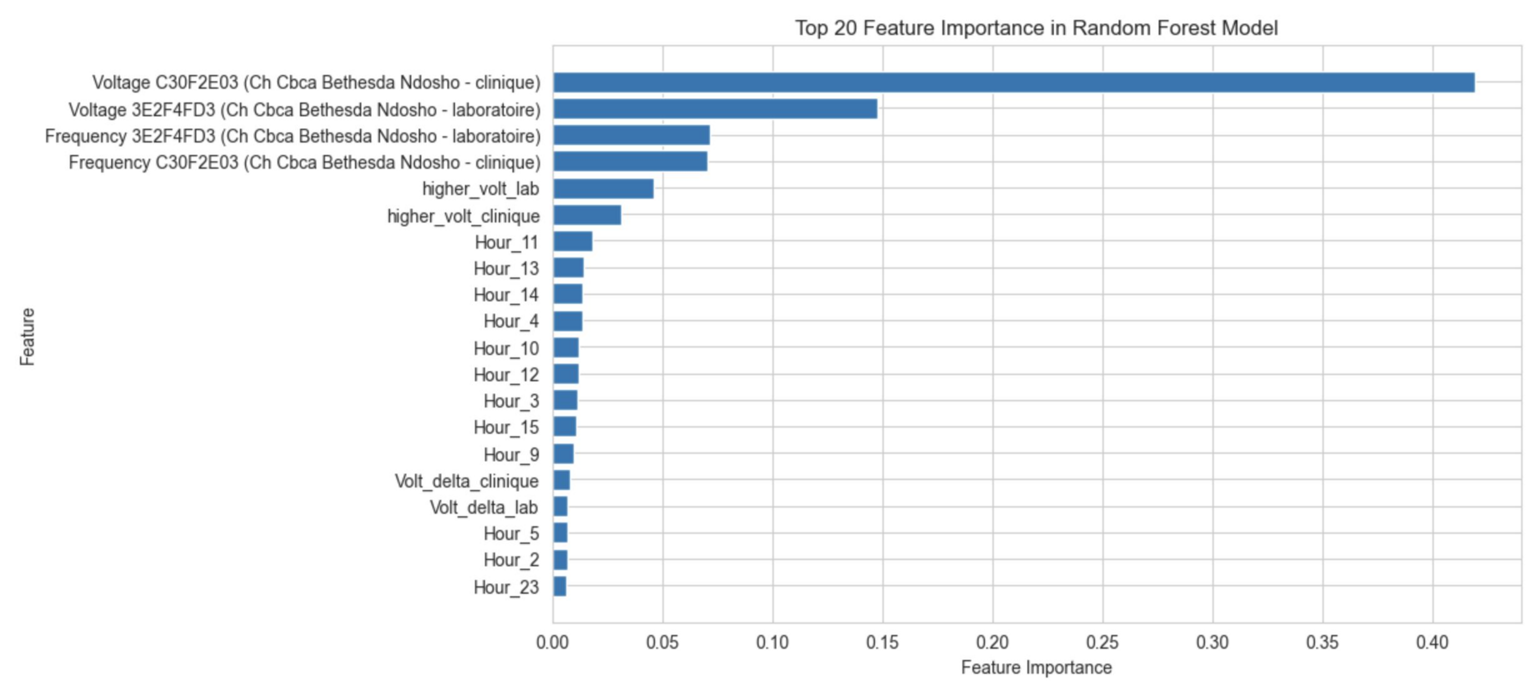
3.2. Time Series - Random Forest



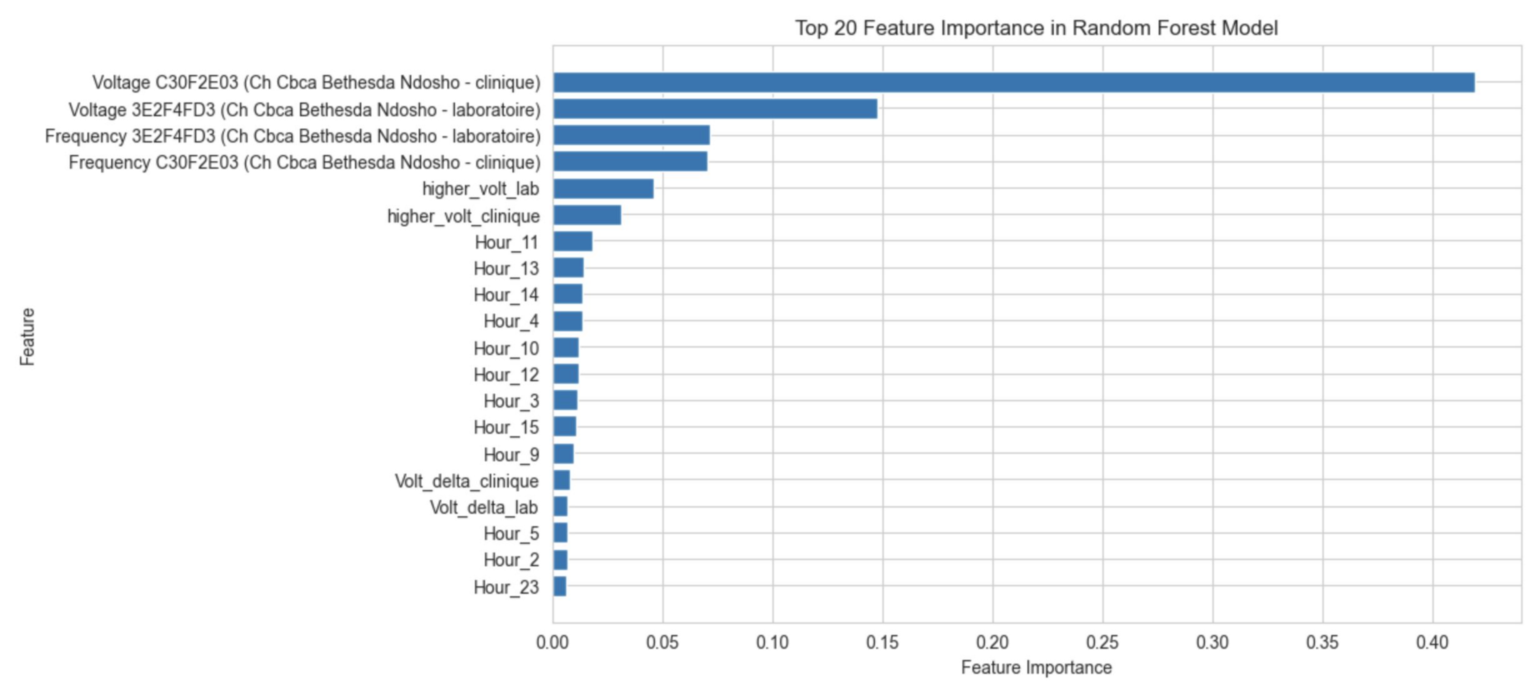
3.2. Time Series - Random Forest



3.2. Time - Series Random Forest



3.2. Random Forest



3.3. Mean Model – XG-Boost (CV'd)

Best parameters: {'colsample_bytree': 0.6, 'gamma': 0, 'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 300, 'reg_alpha': 0, 'reg_lambda': 1, 'subsample': 1.0}

- Train:

```
Train Set Evaluation (XGBoost):
Accuracy: 0.9963624338624338
Confusion Matrix:
[[23138    73]
 [   26  3979]]
Precision: 0.9819842053307009
Recall: 0.9935081148564294
Train data prediction distribution (XGBoost):
prediction
0    23164
1     4052
Name: count, dtype: int64
```

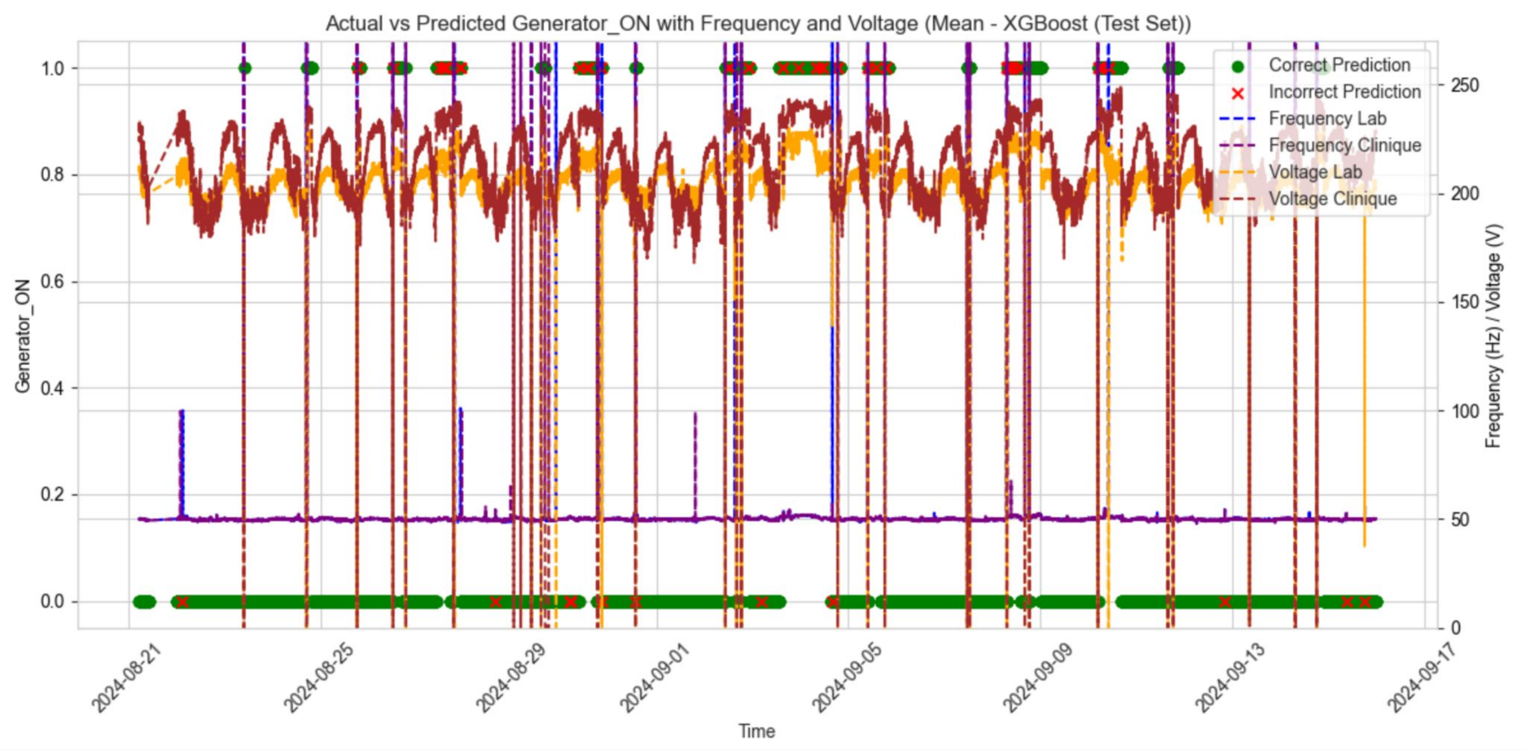
- Test:

```
Test Set Evaluation (XGBoost):
Accuracy: 0.9939925044091711
Confusion Matrix:
[[14802    16]
 [   93  3233]]
Precision: 0.9950754078177901
Recall: 0.9720384846662657
Test data prediction distribution (XGBoost):
prediction
0    14895
1     3249
Name: count, dtype: int64
```

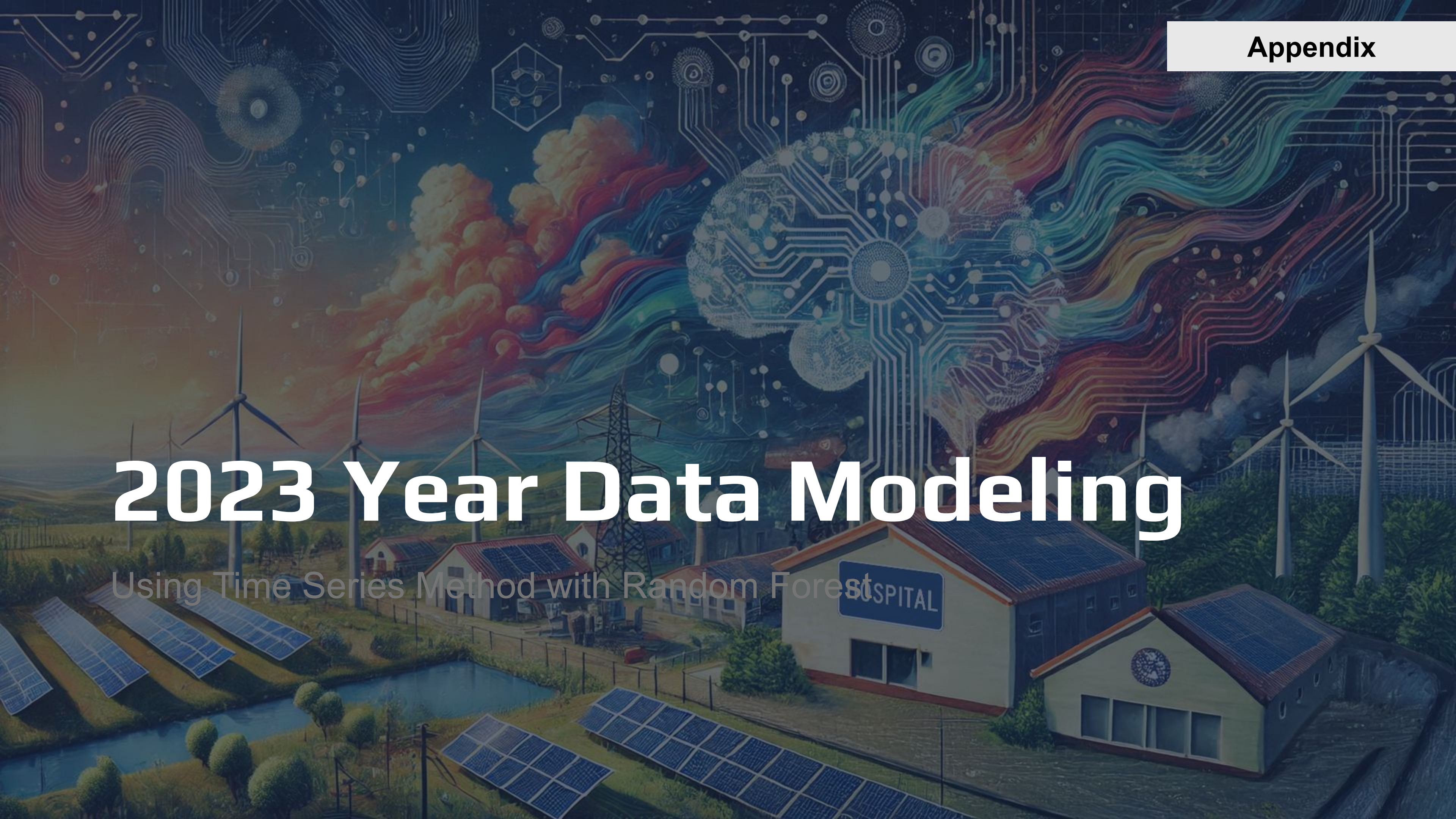
3.3. Mean Model – XG-Boost (CV'd)

```
Classification Report:
              precision    recall  f1-score   support

       False       0.99      1.00      1.00     14818
        True       1.00      0.97      0.98      3326

    accuracy                           0.99     18144
   macro avg       0.99      0.99      0.99     18144
weighted avg       0.99      0.99      0.99     18144

AUC-ROC Score:
0.9994967298957964
Confusion Matrix:
[[14802    16]
 [   93  3233]]
```

3.3. Mean Model – XG-Boost (CV'd)



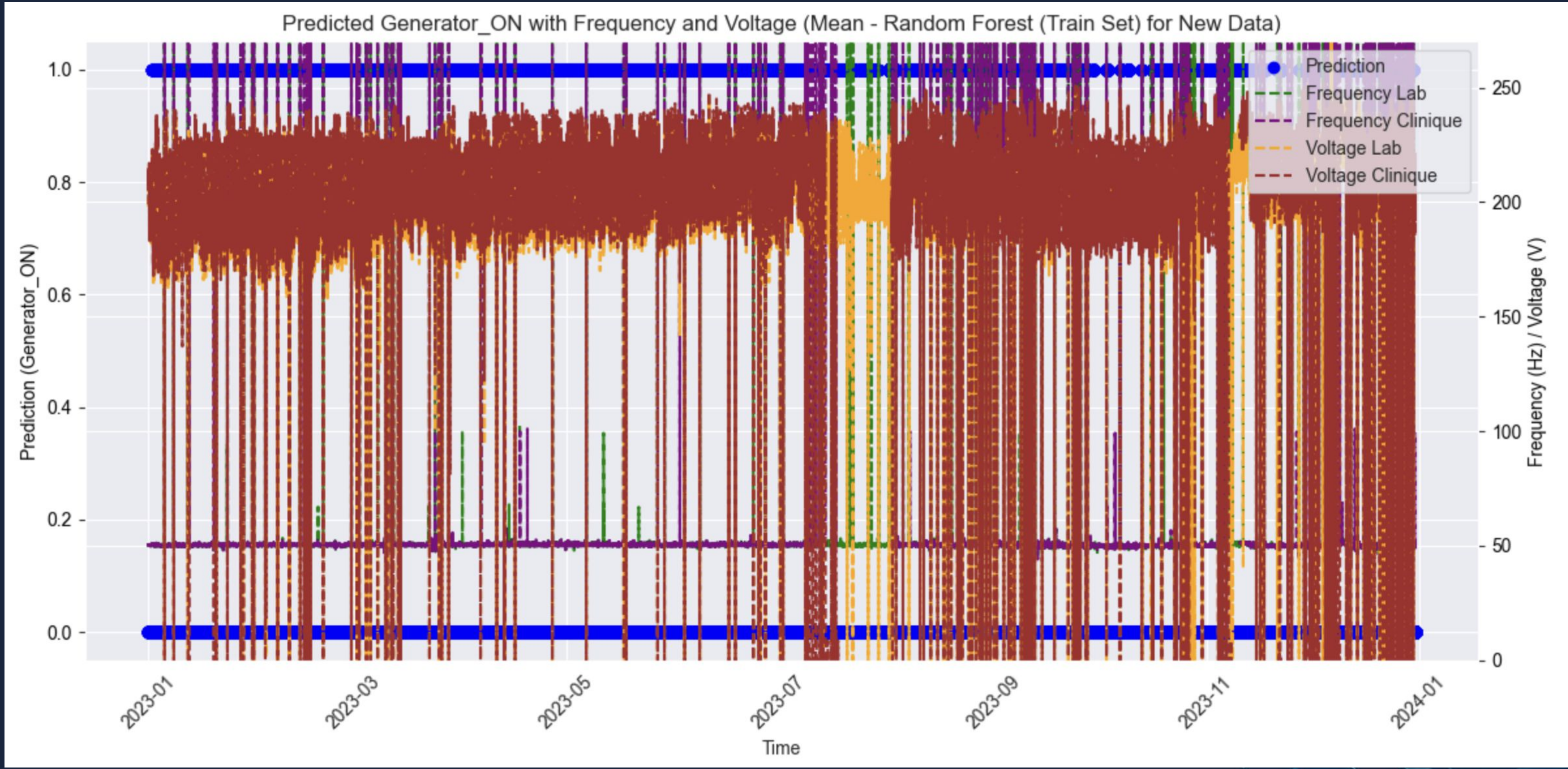
Appendix



2023 Year Data Modeling

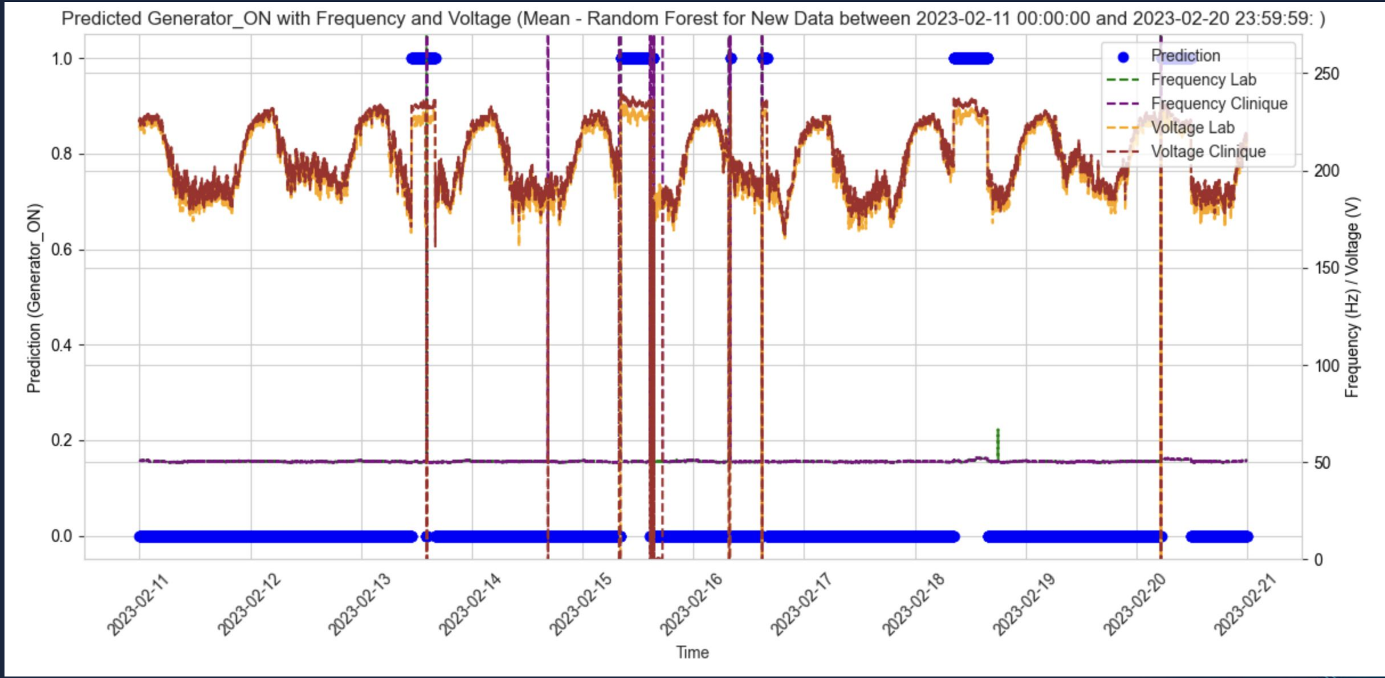
Using Time Series Method with Random Forest

Result: 2023 Data Modeling

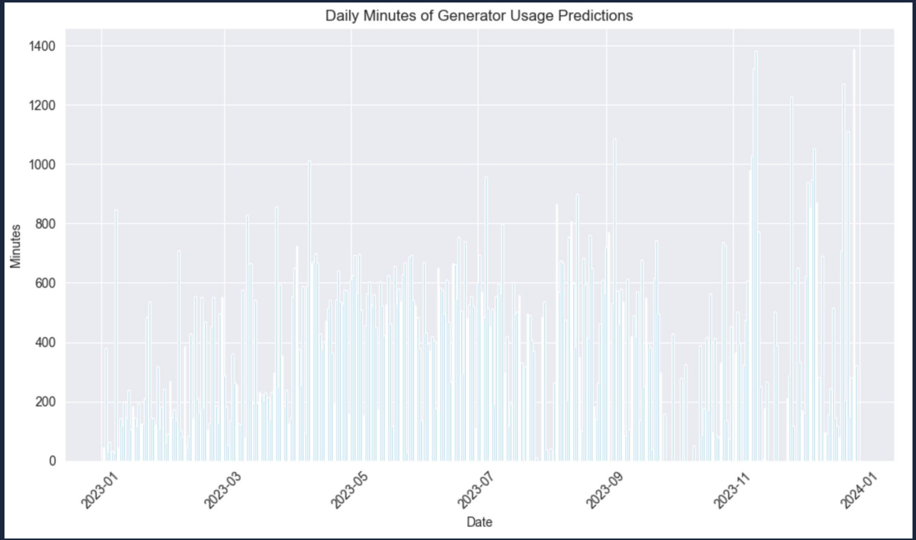


Result: 1 Year – 2023 Data Modeling

Visualization : 11th - 20th February 2023



Result: 1 Year – 2023 Data Modeling

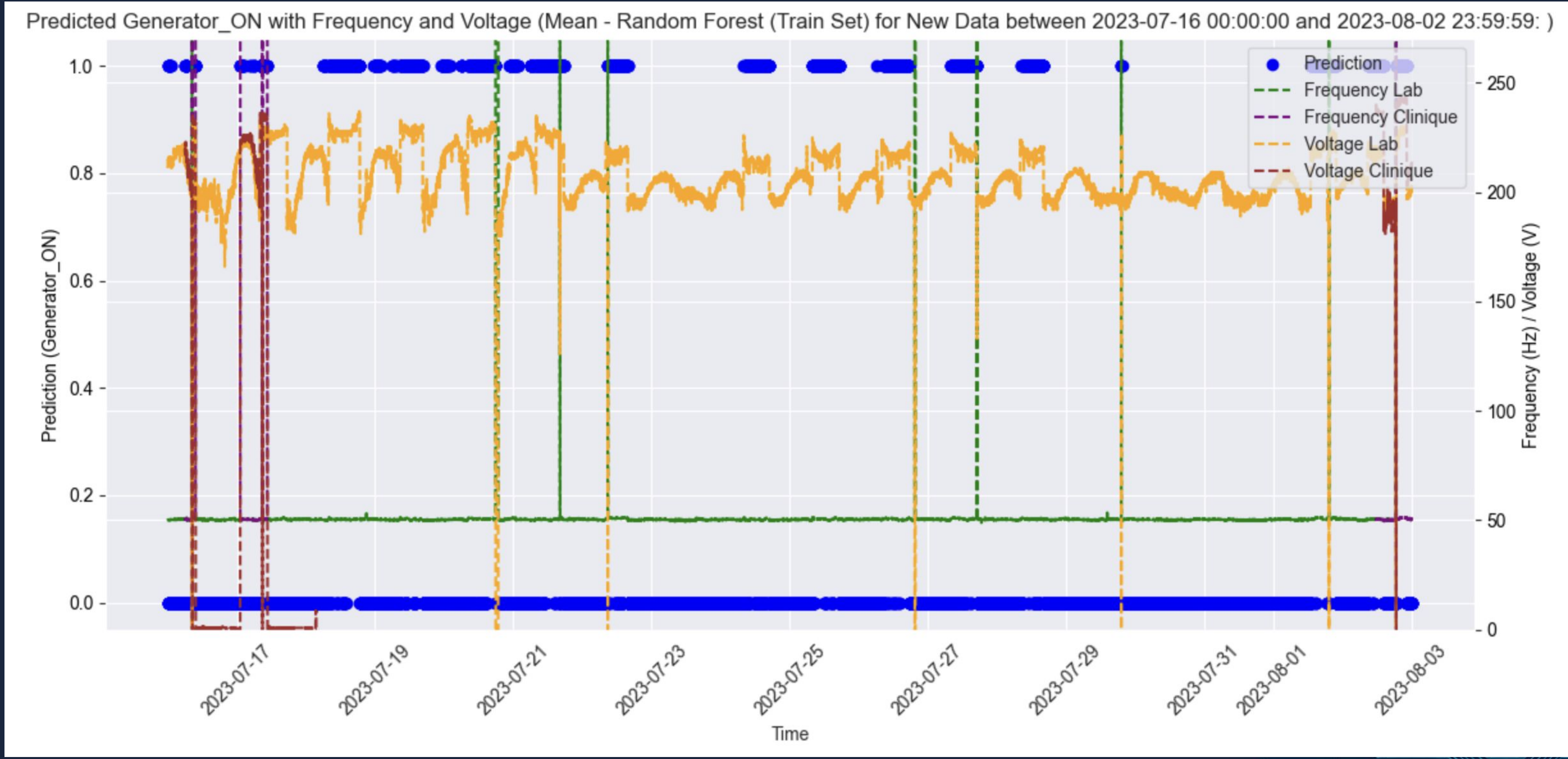


	Date	Count	Minutes	Hours
0	2023-01-02	22	44	0.733333
1	2023-01-03	190	380	6.333333
2	2023-01-04	17	34	0.566667
3	2023-01-05	32	64	1.066667
4	2023-01-06	16	32	0.533333
5	2023-01-07	14	28	0.466667
6	2023-01-08	424	848	14.133333
7	2023-01-09	23	46	0.766667
8	2023-01-10	72	144	2.400000
9	2023-01-11	59	118	1.966667

```
##### PREDICTION RESULT #####
Predicted Minutes: 140304 minutes, or 2338.40 hours within 8904.00 hours
```

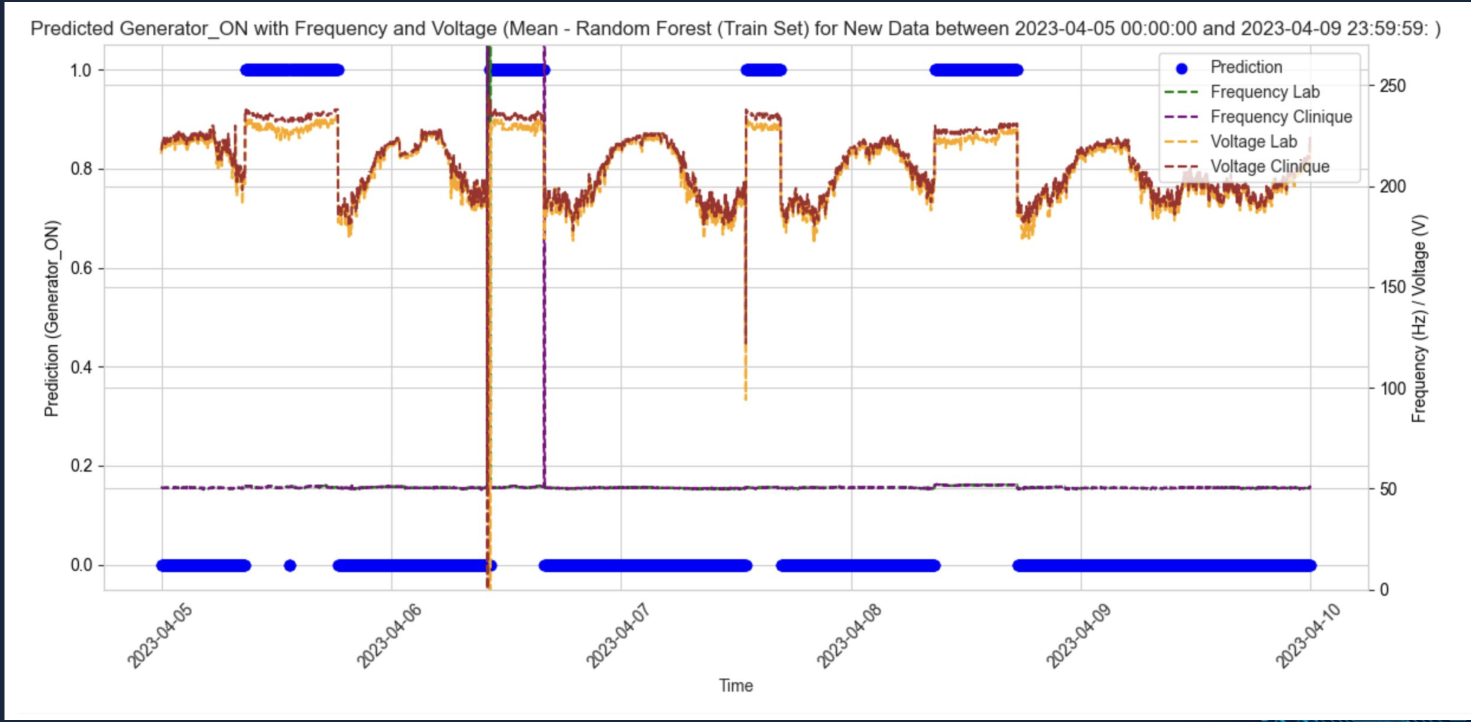
Result: 1 Year – 2023 Data Modeling

Prediction when lost of sensor data on the Clinique between 16th of July to 2nd of August.



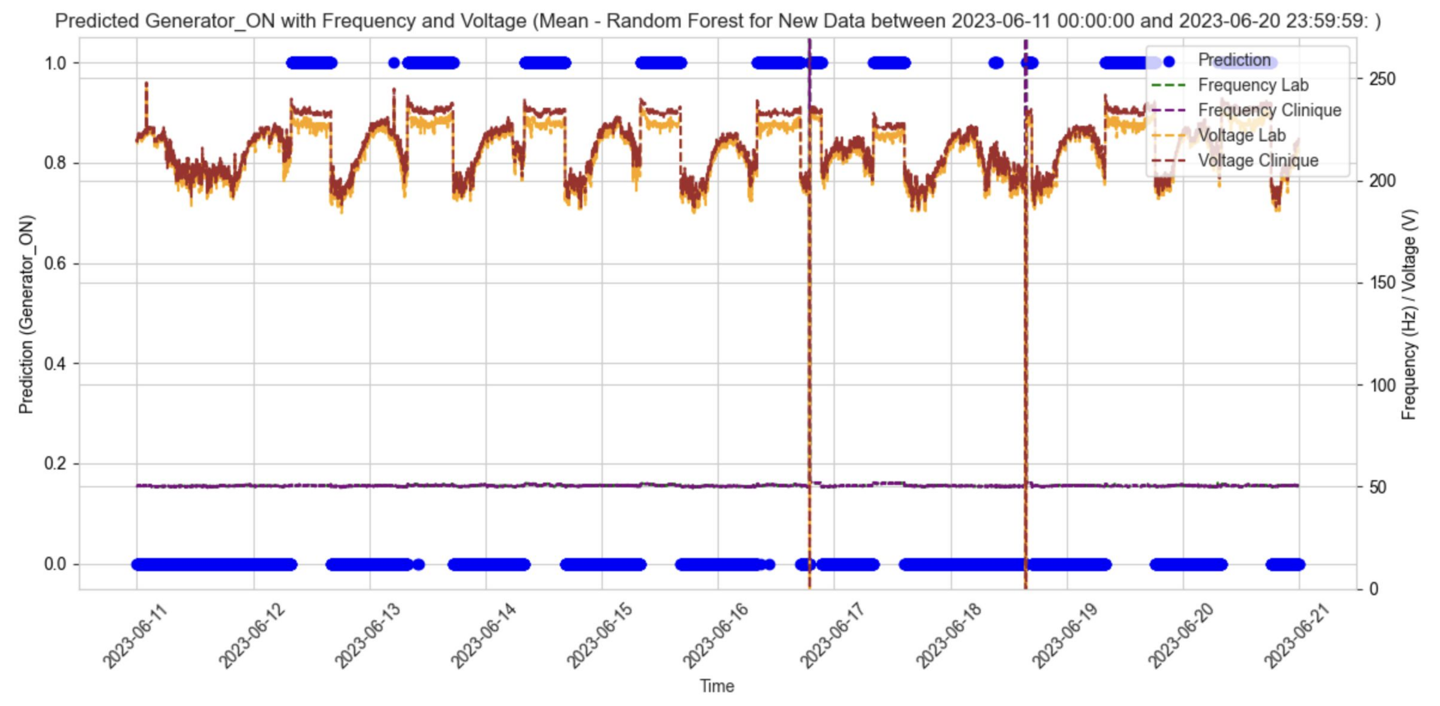
Result: 1 Year – 2023 Data Modeling

April 2023



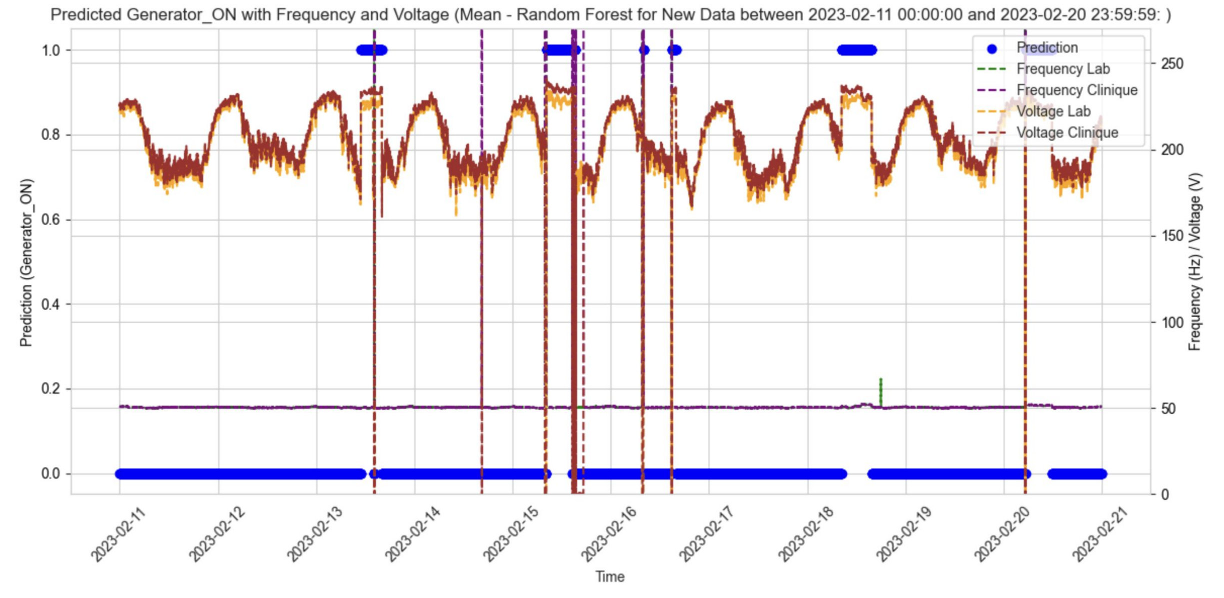
Result: 1 Year – 2023 Data Modeling

June 2023



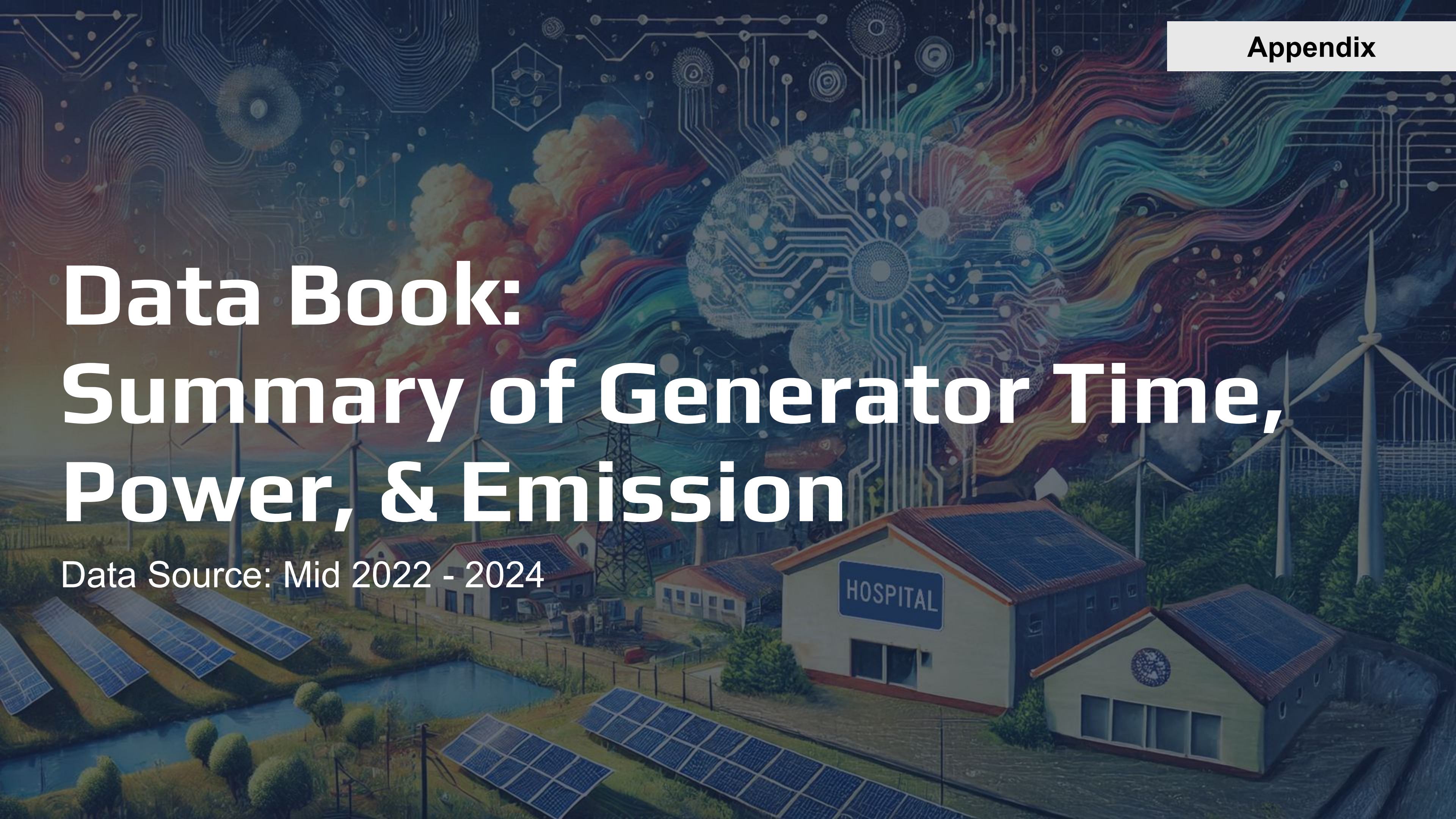
Result: 1 Year – 2023 Data Modeling

Visualization : 11th - 20th February 2023



Data Book: Summary of Generator Time, Power, & Emission

Data Source: Mid 2022 - 2024



Appendix

30th May - 31st December 2022

Appendix

Time (Minutes)

'Yearly Summary:'

5 rows × 2 columns

	Metric	Value
0	Total Minutes Used (min)	28878
1	Average Daily Usage (min)	132.46789
2	Median Daily Usage (min)	6.0
3	Highest Month (Total)	Month 11 (6228 mins)
4	Lowest Month (Total)	Month 5 (270 mins)

'Monthly Summary:'

8 rows × 5 columns

	Month	Total Usage (min)	Average Daily Usage (min)	Max Daily Usage (min)	Max Daily Usage (Date)
0	5	270	33.750000	127	2022-05-30
1	6	5530	92.166667	549	2022-06-06
2	7	3128	50.451613	194	2022-07-28
3	8	3170	51.129032	352	2022-08-25
4	9	4828	80.466667	277	2022-09-21
5	10	3676	59.290323	243	2022-10-30
6	11	6228	103.800000	405	2022-11-07
7	12	2048	33.032258	276	2022-12-05

Power (kWh)

*not kW but kWh

Appendix

'Yearly Summary:'

5 rows × 2 columns

	Metric	Value
0	Total Power Used (kW)	5445.4
1	Average Daily Usage (kW)	24.98
2	Median Daily Usage (kW)	1.02
3	Highest Month (Total)	Month 11 (1195.95 kW)
4	Lowest Month (Total)	Month 5 (61.11 kW)

'Monthly Summary:'

8 rows × 5 columns

	Month	Total Usage (kW)	Average Daily Usage (kW)	Max Daily Usage (kW)	Max Daily Usage (Date)
0	5	61.11	15.28	57.53	2022-05-30
1	6	1058.49	35.28	203.53	2022-06-06
2	7	522.44	16.85	77.81	2022-07-09
3	8	514.09	16.58	143.55	2022-08-25
4	9	935.54	31.18	113.25	2022-09-21
5	10	723.84	23.35	103.34	2022-10-30
6	11	1195.95	39.86	155.18	2022-11-25
7	12	433.95	14.00	116.33	2022-12-05

Appendix

CO2 Emission

'Yearly Summary CO2 emission:'

5 rows × 2 columns

	Metric	Value
0	Total year CO2 Emission (g)	3842219.14
1	Average Daily CO2 Emission (g)	17624.86
2	Median Daily CO2 Emission (g)	719.74
3	Highest Month CO2 Emission (Total)	Month 11 (843848.53 g)
4	Lowest Month CO2 Emission (Total)	Month 5 (43118.71 g)

'Monthly Summary CO2 emission:'

8 rows × 5 columns

	Month	Total CO2 Emission (g)	Average Daily CO2 Emission (g)	Max Daily CO2 Emission (g)	Max Daily CO2 Emission (Date)
0	5	43118.71	10779.68	40593.30	2022-05-30
1	6	746859.59	24895.32	143608.71	2022-06-06
2	7	368626.72	11891.18	54899.83	2022-07-09
3	8	362734.48	11701.11	101285.54	2022-08-25
4	9	660107.43	22003.58	79905.20	2022-09-21
5	10	510735.62	16475.34	72916.33	2022-10-30
6	11	843848.53	28128.28	109493.22	2022-11-25
7	12	306188.06	9877.03	82083.50	2022-12-05

Appendix

NOx Emission

'Yearly Summary NOx emission:'

5 rows × 2 columns

	Metric	Value
0	Total year NOx Emission (g)	79494.19
1	Average Daily NOx Emission (g)	364.65
2	Median Daily NOx Emission (g)	14.89
3	Highest Month NOx Emission (Total)	Month 11 (17458.94 g)
4	Lowest Month NOx Emission (Total)	Month 5 (892.11 g)

'Monthly Summary NOx emission:'

8 rows × 5 columns

Static Output

	Month	Total NOx Emission (g)	Average Daily NOx Emission (g)	Max Daily NOx Emission (g)	Max Daily NOx Emission (Date)
0	5	892.11	223.03	839.86	2022-05-30
1	6	15452.27	515.08	2971.21	2022-06-06
2	7	7626.76	246.02	1135.86	2022-07-09
3	8	7504.85	242.09	2095.56	2022-08-25
4	9	13657.40	455.25	1653.21	2022-09-21
5	10	10566.94	340.87	1508.61	2022-10-30
6	11	17458.94	581.96	2265.38	2022-11-25
7	12	6334.93	204.35	1698.28	2022-12-05

CO Emission

'Yearly Summary CO emission:'

5 rows ∨ 5 rows × 2 columns

	Metric	Value
0	Total year CO Emission (g)	18217.42
1	Average Daily CO Emission (g)	83.57
2	Median Daily CO Emission (g)	3.41
3	Highest Month CO Emission (Total)	Month 11 (4001.01 g)
4	Lowest Month CO Emission (Total)	Month 5 (204.44 g)

'Monthly Summary CO emission:'

8 rows ∨ 8 rows × 5 columns Stati

	Month	Total CO Emission (g)	Average Daily CO Emission (g)	Max Daily CO Emission (g)	Max Daily CO Emission (Date)
0	5	204.44	51.11	192.47	2022-05-30
1	6	3541.14	118.04	680.90	2022-06-06
2	7	1747.80	56.38	260.30	2022-07-09
3	8	1719.86	55.48	480.23	2022-08-25
4	9	3129.82	104.33	378.86	2022-09-21
5	10	2421.59	78.12	345.72	2022-10-30
6	11	4001.01	133.37	519.15	2022-11-25
7	12	1451.75	46.83	389.19	2022-12-05

SOx Emission

Appendix

'Yearly Summary SOx emission:'

5 rows × 2 columns

	Metric	Value
0	Total year SOx Emission (g)	26796.17
1	Average Daily SOx Emission (g)	122.92
2	Median Daily SOx Emission (g)	5.02
3	Highest Month SOx Emission (Total)	Month 11 (5885.12 g)
4	Lowest Month SOx Emission (Total)	Month 5 (300.72 g)

'Monthly Summary SOx emission:'

8 rows × 5 columns

	Month	Total SOx Emission (g)	Average Daily SOx Emission (g)	Max Daily SOx Emission (g)	Max Daily SOx Emission (Date)
0	5	300.72	75.18	283.10	2022-05-30
1	6	5208.70	173.62	1001.55	2022-06-06
2	7	2570.85	82.93	382.88	2022-07-09
3	8	2529.76	81.61	706.38	2022-08-25
4	9	4603.68	153.46	557.27	2022-09-21
5	10	3561.94	114.90	508.53	2022-10-30
6	11	5885.12	196.17	763.62	2022-11-25
7	12	2135.40	68.88	572.46	2022-12-05

PM Emission

'Yearly Summary PM emission:'

5 rows × 2 columns

	Metric	Value
0	Total year PM Emission (g)	2318.58
1	Average Daily PM Emission (g)	10.64
2	Median Daily PM Emission (g)	0.43
3	Highest Month PM Emission (Total)	Month 11 (509.22 g)
4	Lowest Month PM Emission (Total)	Month 5 (26.02 g)

'Monthly Summary PM emission:'

8 rows × 5 columns

	Month	Total PM Emission (g)	Average Daily PM Emission (g)	Max Daily PM Emission (g)	Max Daily PM Emission (Date)
0	5	26.02	6.50	24.50	2022-05-30
1	6	450.69	15.02	86.66	2022-06-06
2	7	222.45	7.18	33.13	2022-07-09
3	8	218.89	7.06	61.12	2022-08-25
4	9	398.34	13.28	48.22	2022-09-21
5	10	308.20	9.94	44.00	2022-10-30
6	11	509.22	16.97	66.07	2022-11-25
7	12	184.77	5.96	49.53	2022-12-05

1st January - 31st December 2023

Time

Appendix

'Yearly Summary:'

5 rows × 2 columns

	Metric	Value
0	Total Minutes Used (min)	113200
1	Average Daily Usage (min)	310.136986
2	Median Daily Usage (min)	302.0
3	Highest Month (Total)	Month 12 (14056 mins)
4	Lowest Month (Total)	Month 1 (2976 mins)

'Monthly Summary:'

12 rows × 5 columns

	Month	Total Usage (min)	Average Daily Usage (min)	Max Daily Usage (min)	Max Daily Usage (Date)
0	1	2976	48.000000	383	2023-01-08
1	2	4422	78.964286	352	2023-02-07
2	3	5000	80.645161	390	2023-03-12
3	4	12872	214.533333	488	2023-04-11
4	5	13516	218.000000	318	2023-05-29
5	6	13428	223.800000	363	2023-06-22
6	7	8388	135.290323	428	2023-07-05
7	8	12276	198.000000	434	2023-08-08
8	9	11912	198.533333	533	2023-09-05
9	10	4918	79.322581	397	2023-10-27
10	11	9436	157.266667	683	2023-11-12

Power (kWh)

*not kW but kWh

Appendix

'Yearly Summary:'

5 rows × 2 columns

	Metric	Value
0	Total Power Used (kW)	22294.77
1	Average Daily Usage (kW)	61.08
2	Median Daily Usage (kW)	60.68
3	Highest Month (Total)	Month 5 (2830.83 kW)
4	Lowest Month (Total)	Month 1 (571.2 kW)

'Monthly Summary:'

12 rows × 5 columns

	Month	Total Usage (kW)	Average Daily Usage (kW)	Max Daily Usage (kW)	Max Daily Usage (Date)
0	1	571.20	18.43	150.45	2023-01-08
1	2	911.07	32.54	144.18	2023-02-07
2	3	969.49	31.27	145.24	2023-03-12
3	4	2635.32	87.84	190.79	2023-04-11
4	5	2830.83	91.32	132.65	2023-05-29
5	6	2798.46	93.28	142.69	2023-06-22
6	7	1732.21	55.88	155.19	2023-07-05
7	8	2350.87	75.83	152.06	2023-08-18
8	9	2374.75	79.16	200.91	2023-09-05
9	10	969.79	31.28	149.74	2023-10-27
10	11	1679.03	55.97	232.71	2023-11-12
11	12	2471.75	79.73	232.28	2023-12-29

CO2 Emission

'Yearly Summary CO2 emission:'

5 rows × 2 columns

	Metric	Value
0	Total year CO2 Emission (g)	15768619.23
1	Average Daily CO2 Emission (g)	43201.7
2	Median Daily CO2 Emission (g)	42862.21
3	Highest Month CO2 Emission (Total)	Month 5 (1998829.42 g)
4	Lowest Month CO2 Emission (Total)	Month 1 (404486.28 g)

'Monthly Summary CO2 emission:'

12 rows × 5 columns

Static Output

Month	Total CO2 Emission (g)	Average Daily CO2 Emission (g)	Max Daily CO2 Emission (g)	Max Daily CO2 Emission (Date)
1	404486.28	13047.94	106449.95	2023-01-08
2	644085.68	23003.06	102061.18	2023-02-07
3	686319.92	22139.35	102889.07	2023-03-12
4	1860947.81	62031.59	135021.62	2023-04-11
5	1998829.42	64478.37	93848.12	2023-05-29
6	1975942.44	65864.75	100889.90	2023-06-22
7	1223024.28	39452.40	109996.71	2023-07-05
8	1664676.31	53699.24	107790.57	2023-08-18
9	1679138.54	55971.28	142510.28	2023-09-05
10	686230.55	22136.47	106083.04	2023-10-27
11	1191371.53	39712.38	165286.71	2023-11-12
12	1753566.48	56566.66	164722.24	2023-12-29

NOx Emission

'Yearly Summary NOx emission:'

5 rows × 2 columns

	Metric	Value
0	Total year NOx Emission (g)	326247.29
1	Average Daily NOx Emission (g)	893.83
2	Median Daily NOx Emission (g)	886.8
3	Highest Month NOx Emission (Total)	Month 5 (41355.09 g)
4	Lowest Month NOx Emission (Total)	Month 1 (8368.68 g)

'Monthly Summary NOx emission:'

12 rows × 5 columns

Static Output

Month	Total NOx Emission (g)	Average Daily NOx Emission (g)	Max Daily NOx Emission (g)	Max Daily NOx Emission (Date)
1	8368.68	269.96	2202.41	2023-01-08
2	13325.91	475.93	2111.61	2023-02-07
3	14199.72	458.06	2128.74	2023-03-12
4	38502.37	1283.41	2793.55	2023-04-11
5	41355.09	1334.04	1941.69	2023-05-29
6	40881.57	1362.72	2087.38	2023-06-22
7	25303.95	816.26	2275.79	2023-07-05
8	34441.58	1111.02	2230.15	2023-08-18
9	34740.80	1158.03	2948.49	2023-09-05
10	14197.87	458.00	2194.82	2023-10-27
11	24649.07	821.64	3419.73	2023-11-12
12	36280.69	1170.34	3408.05	2023-12-29

CO Emission

'Yearly Summary CO emission:'

5 rows × 2 columns

	Metric	Value
0	Total year CO Emission (g)	74765.0
1	Average Daily CO Emission (g)	204.84
2	Median Daily CO Emission (g)	203.23
3	Highest Month CO Emission (Total)	Month 5 (9477.21 g)
4	Lowest Month CO Emission (Total)	Month 1 (1917.82 g)

'Monthly Summary CO emission:'

12 rows × 5 columns Static Output

	Month	Total CO Emission (g)	Average Daily CO Emission (g)	Max Daily CO Emission (g)	Max Daily CO Emission (Date)
0	1	1917.82	61.87	504.72	2023-01-08
1	2	3053.85	109.07	483.91	2023-02-07
2	3	3254.10	104.97	487.84	2023-03-12
3	4	8823.46	294.12	640.19	2023-04-11
4	5	9477.21	305.72	444.97	2023-05-29
5	6	9368.69	312.29	478.36	2023-06-22
6	7	5798.82	187.06	521.54	2023-07-05
7	8	7892.86	254.61	511.08	2023-08-18
8	9	7961.43	265.38	675.70	2023-09-05
9	10	3253.68	104.96	502.98	2023-10-27
10	11	5648.74	188.29	783.69	2023-11-12
11	12	8314.32	268.20	781.01	2023-12-29

SOx

'Yearly Summary SOx emission:'

5 rows × 2 columns

	Metric	Value
0	Total year SOx Emission (g)	109972.53
1	Average Daily SOx Emission (g)	301.29
2	Median Daily SOx Emission (g)	298.93
3	Highest Month SOx Emission (Total)	Month 5 (13940.11 g)
4	Lowest Month SOx Emission (Total)	Month 1 (2820.94 g)

'Monthly Summary SOx emission:'

12 rows × 5 columns

Month	Total SOx Emission (g)	Average Daily SOx Emission (g)	Max Daily SOx Emission (g)	Max Daily SOx Emission (Date)
1	2820.94	91.00	742.40	2023-01-08
2	4491.94	160.43	711.79	2023-02-07
3	4786.49	154.40	717.56	2023-03-12
4	12978.51	432.62	941.66	2023-04-11
5	13940.11	449.68	654.51	2023-05-29
6	13780.50	459.35	703.62	2023-06-22
7	8529.54	275.15	767.13	2023-07-05
8	11609.68	374.51	751.75	2023-08-18
9	11710.54	390.35	993.89	2023-09-05
10	4785.87	154.38	739.84	2023-10-27
11	8308.79	276.96	1152.73	2023-11-12
12	12229.61	394.50	1148.80	2023-12-29

PM Emission

'Yearly Summary PM emission:'

5 rows × 2 columns

	Metric	Value
0	Total year PM Emission (g)	9515.55
1	Average Daily PM Emission (g)	26.07
2	Median Daily PM Emission (g)	25.87
3	Highest Month PM Emission (Total)	Month 5 (1206.19 g)
4	Lowest Month PM Emission (Total)	Month 1 (244.09 g)

'Monthly Summary PM emission:'

12 rows × 5 columns

Static Output

	Month	Total PM Emission (g)	Average Daily PM Emission (g)	Max Daily PM Emission (g)	Max Daily PM Emission (Date)
0	1	244.09	7.87	64.24	2023-01-08
1	2	388.67	13.88	61.59	2023-02-07
2	3	414.16	13.36	62.09	2023-03-12
3	4	1122.99	37.43	81.48	2023-04-11
4	5	1206.19	38.91	56.63	2023-05-29
5	6	1192.38	39.75	60.88	2023-06-22
6	7	738.03	23.81	66.38	2023-07-05
7	8	1004.55	32.40	65.05	2023-08-18
8	9	1013.27	33.78	86.00	2023-09-05
9	10	414.10	13.36	64.02	2023-10-27
10	11	718.93	23.96	99.74	2023-11-12
11	12	1058.19	34.14	99.40	2023-12-29

1st January - 10th November 2024

Time

'Yearly Summary:'

5 rows × 2 columns

	Metric	Value
0	Total Minutes Used (min)	82944
1	Average Daily Usage (min)	263.314286
2	Median Daily Usage (min)	174.0
3	Highest Month (Total)	Month 9 (15886 mins)
4	Lowest Month (Total)	Month 11 (3540 mins)

'Monthly Summary:'

11 rows × 5 columns

	Month	Total Usage (min)	Average Daily Usage (min)	Max Daily Usage (min)	Max Daily Usage (Date)
0	1	7308	117.870968	340	2024-01-19
1	2	5284	91.103448	295	2024-02-27
2	3	5262	84.870968	332	2024-03-30
3	4	8110	135.166667	467	2024-04-15
4	5	5372	86.645161	389	2024-05-10
5	6	6442	107.366667	300	2024-06-04
6	7	5308	85.612903	320	2024-07-07
7	8	8102	130.677419	441	2024-08-20
8	9	15886	264.766667	720	2024-09-25
9	10	12330	198.870968	666	2024-10-11
10	11	3540	177.000000	307	2024-11-06

Appendix

Power (kWh)

*not kW but kWh

'Yearly Summary:'

5 rows × 2 columns

	Metric	Value
0	Total Power Used (kW)	15322.59
1	Average Daily Usage (kW)	48.64
2	Median Daily Usage (kW)	28.94
3	Highest Month (Total)	Month 9 (2745.76 kW)
4	Lowest Month (Total)	Month 11 (693.58 kW)

'Monthly Summary:'

11 rows × 5 columns

	Month	Total Usage (kW)	Average Daily Usage (kW)	Max Daily Usage (kW)	Max Daily Usage (Date)
0	1	1335.60	43.08	123.74	2024-01-19
1	2	972.23	33.53	122.42	2024-02-27
2	3	1082.42	34.92	132.66	2024-03-22
3	4	1596.87	53.23	160.08	2024-04-15
4	5	1055.84	34.06	130.77	2024-05-10
5	6	1273.37	42.45	122.28	2024-06-04
6	7	976.47	31.50	131.35	2024-07-07
7	8	1444.78	46.61	176.15	2024-08-20
8	9	2745.76	91.53	244.59	2024-09-25
9	10	2145.67	69.22	228.35	2024-10-11
10	11	693.58	69.36	119.78	2024-11-04

CO2 Emission

'Yearly Summary CO2 emission:'

5 rows × 2 columns

	Metric	Value
0	Total year CO2 Emission (g)	10859917.25
1	Average Daily CO2 Emission (g)	34475.93
2	Median Daily CO2 Emission (g)	20643.2
3	Highest Month CO2 Emission (Total)	Month 9 (1950654.11 g)
4	Lowest Month CO2 Emission (Total)	Month 11 (490951.58 g)

'Monthly Summary CO2 emission:'

11 rows × 5 columns

Month	Total CO2 Emission (g)	Average Daily CO2 Emission (g)	Max Daily CO2 Emission (g)	Max Daily CO2 Emission (Date)
1	947047.03	30549.90	87695.38	2024-01-19
2	689241.06	23766.93	86528.80	2024-02-27
3	764692.11	24667.49	93866.93	2024-03-22
4	1128708.12	37623.60	113646.96	2024-04-15
5	747019.44	24097.40	92963.78	2024-05-10
6	900412.26	30013.74	86552.32	2024-06-04
7	692594.96	22341.77	92817.96	2024-07-07
8	1024788.89	33057.71	124705.90	2024-08-20
9	1950654.11	65021.80	173786.71	2024-09-25
10	1523807.70	49155.09	162278.55	2024-10-11
11	490951.58	49095.16	84560.21	2024-11-04

NOx Emission

Appendix

'Yearly Summary NOx emission:'

5 rows × 2 columns

	Metric	Value
0	Total year NOx Emission (g)	224687.94
1	Average Daily NOx Emission (g)	713.3
2	Median Daily NOx Emission (g)	427.1
3	Highest Month NOx Emission (Total)	Month 9 (40358.36 g)
4	Lowest Month NOx Emission (Total)	Month 11 (10157.62 g)

'Monthly Summary NOx emission:'

11 rows × 5 columns Static Output

Month	Total NOx Emission (g)	Average Daily NOx Emission (g)	Max Daily NOx Emission (g)	Max Daily NOx Emission (Date)
1	19594.08	632.07	1814.39	2024-01-19
2	14260.16	491.73	1790.25	2024-02-27
3	15821.22	510.36	1942.07	2024-03-22
4	23352.58	778.42	2351.32	2024-04-15
5	15455.57	498.57	1923.39	2024-05-10
6	18629.22	620.97	1790.74	2024-06-04
7	14329.55	462.24	1920.37	2024-07-07
8	21202.53	683.95	2580.12	2024-08-20
9	40358.36	1345.28	3595.59	2024-09-25
10	31527.06	1017.00	3357.49	2024-10-11
11	10157.62	1015.76	1749.52	2024-11-04

CO Emission

Appendix

'Yearly Summary CO emission:'

5 rows × 2 columns

	Metric	Value
0	Total year CO Emission (g)	51490.99
1	Average Daily CO Emission (g)	163.46
2	Median Daily CO Emission (g)	97.88
3	Highest Month CO Emission (Total)	Month 9 (9248.79 g)
4	Lowest Month CO Emission (Total)	Month 11 (2327.79 g)

'Monthly Summary CO emission:'

11 rows × 5 columns

Static Output

	Month	Total CO Emission (g)	Average Daily CO Emission (g)	Max Daily CO Emission (g)	Max Daily CO Emission (Date)
0	1	4490.31	144.85	415.80	2024-01-19
1	2	3267.95	112.69	410.27	2024-02-27
2	3	3625.70	116.96	445.06	2024-03-22
3	4	5351.63	178.39	538.84	2024-04-15
4	5	3541.90	114.25	440.78	2024-05-10
5	6	4269.20	142.31	410.38	2024-06-04
6	7	3283.86	105.93	440.09	2024-07-07
7	8	4858.91	156.74	591.28	2024-08-20
8	9	9248.79	308.29	823.99	2024-09-25
9	10	7224.95	233.06	769.42	2024-10-11
10	11	2327.79	232.78	400.93	2024-11-04

SOx Emission

'Yearly Summary SOx emission:'

5 rows × 2 columns

	Metric	Value
0	Total year SOx Emission (g)	75738.56
1	Average Daily SOx Emission (g)	240.44
2	Median Daily SOx Emission (g)	143.97
3	Highest Month SOx Emission (Total)	Month 9 (13604.13 g)
4	Lowest Month SOx Emission (Total)	Month 11 (3423.96 g)

'Monthly Summary SOx emission:'

11 rows × 5 columns Static Output

Month	Total SOx Emission (g)	Average Daily SOx Emission (g)	Max Daily SOx Emission (g)	Max Daily SOx Emission (Date)
1	6604.84	213.06	611.60	2024-01-19
2	4806.86	165.75	603.46	2024-02-27
3	5333.07	172.03	654.64	2024-03-22
4	7871.77	262.39	792.59	2024-04-15
5	5209.82	168.06	648.34	2024-05-10
6	6279.60	209.32	603.63	2024-06-04
7	4830.25	155.81	647.33	2024-07-07
8	7147.02	230.55	869.72	2024-08-20
9	13604.13	453.47	1212.01	2024-09-25
10	10627.25	342.81	1131.75	2024-10-11
11	3423.96	342.40	589.73	2024-11-04

PM Emission

'Yearly Summary PM emission:'

5 rows × 2 columns

	Metric	Value
0	Total year PM Emission (g)	6553.4
1	Average Daily PM Emission (g)	20.8
2	Median Daily PM Emission (g)	12.46
3	Highest Month PM Emission (Total)	Month 9 (1177.12 g)
4	Lowest Month PM Emission (Total)	Month 11 (296.26 g)

'Monthly Summary PM emission:'

11 rows × 5 columns

Static Output

	Month	Total PM Emission (g)	Average Daily PM Emission (g)	Max Daily PM Emission (g)	Max Daily PM Emission (Date)
0	1	571.49	18.44	52.92	2024-01-19
1	2	415.92	14.34	52.22	2024-02-27
2	3	461.45	14.89	56.64	2024-03-22
3	4	681.12	22.70	68.58	2024-04-15
4	5	450.79	14.54	56.10	2024-05-10
5	6	543.35	18.11	52.23	2024-06-04
6	7	417.95	13.48	56.01	2024-07-07
7	8	618.41	19.95	75.25	2024-08-20
8	9	1177.12	39.24	104.87	2024-09-25
9	10	919.54	29.66	97.93	2024-10-11
10	11	296.26	29.63	51.03	2024-11-04