# A Machine Learning Pipeline for the Preventive Maintenance of a Building HVAC System

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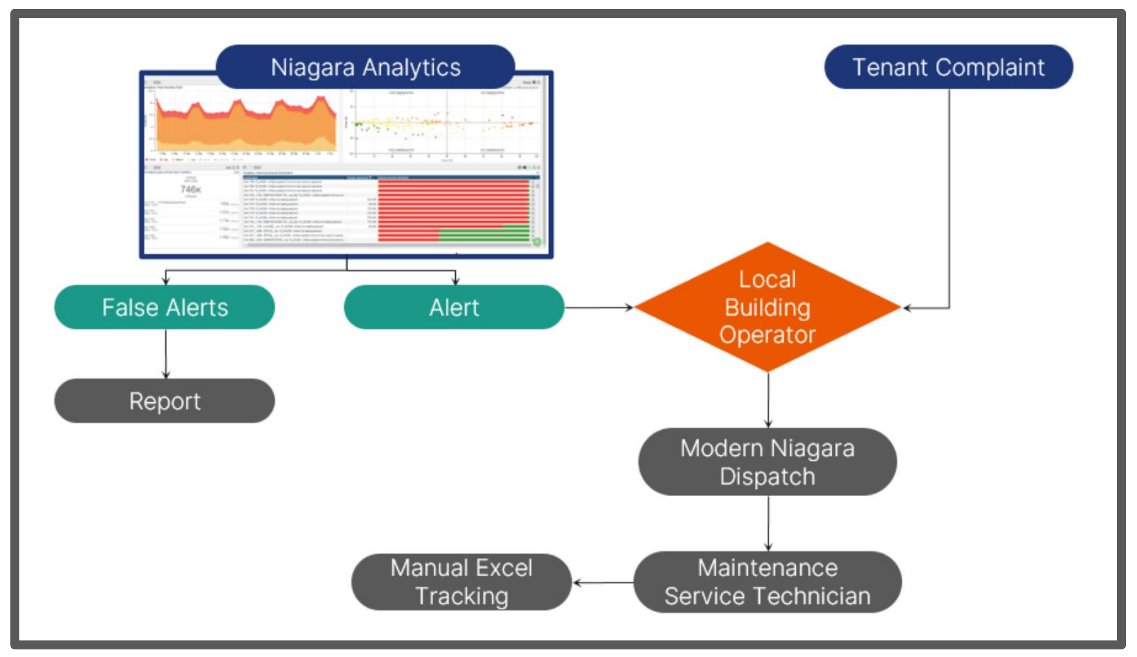
## Problem Statement

For maintenance issues such as abrupt faults, Modern Niagara Group (MNG) is reliant on the customer's local building operator to place a call to MNG's 24/7 dispatch for reactive service.
This results in delays in regular building activities which are:

- Costly
- Detrimental to customer satisfaction




## Objectives

Create a proof-of-concept that can identify potential building maintenance failures before they occur, without manual intervention.

- **Autonomous:** No human intervention required.
- **Reliable:** Training Accuracy > 90%.
- **Modular:** Can be separated into components.
- **Computationally Efficient:** >16 RAM

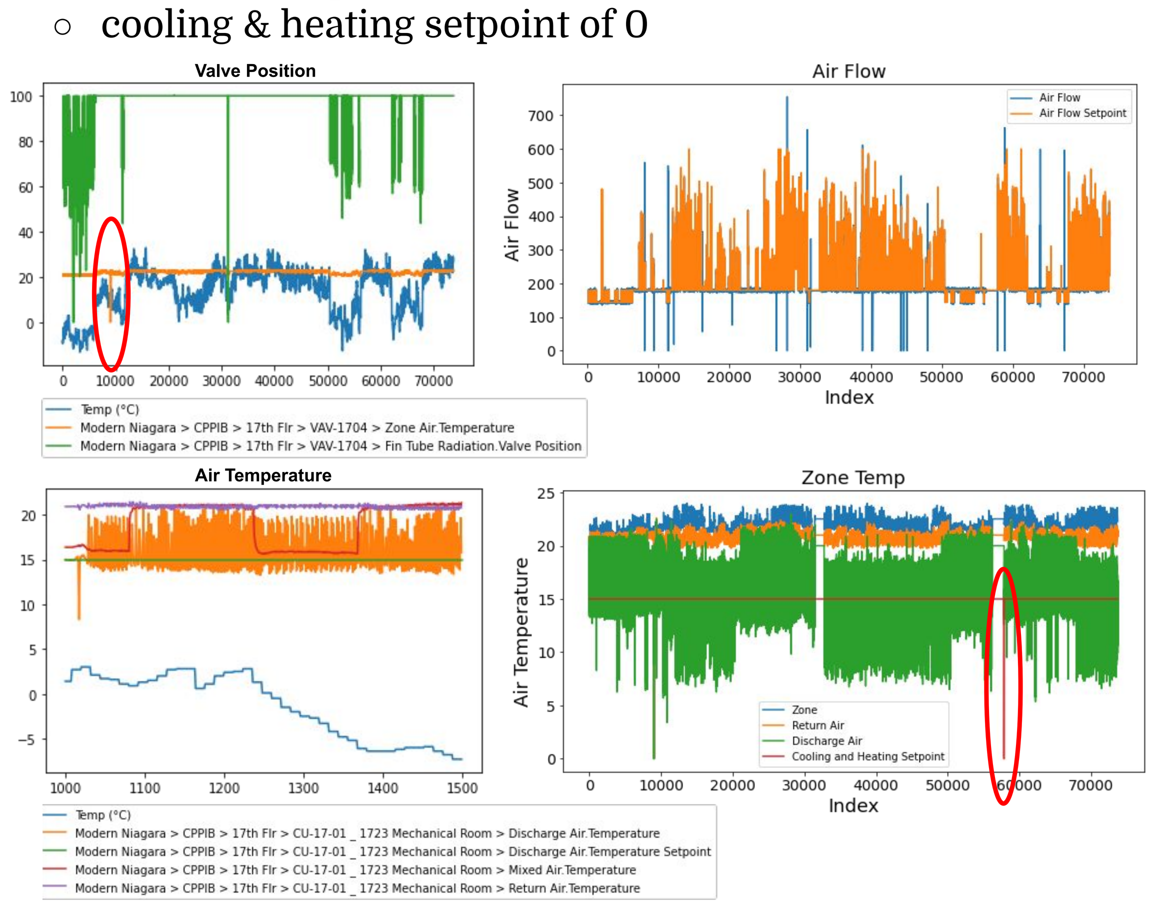
## Exploratory Data Analysis

Datasets Used

- HVAC Sensor data from 1 central unit and 42 variable air boxes from the 17th floor of the CPPIB building over a 10-month period
- Weather data for Toronto City Centre from Environment Canada (historical and forecast)

Data Cleaning

- identified and removed outliers that are caused by human intervention or sensor error
  - zone-air temperature of 0
  - cooling & heating setpoint of 0



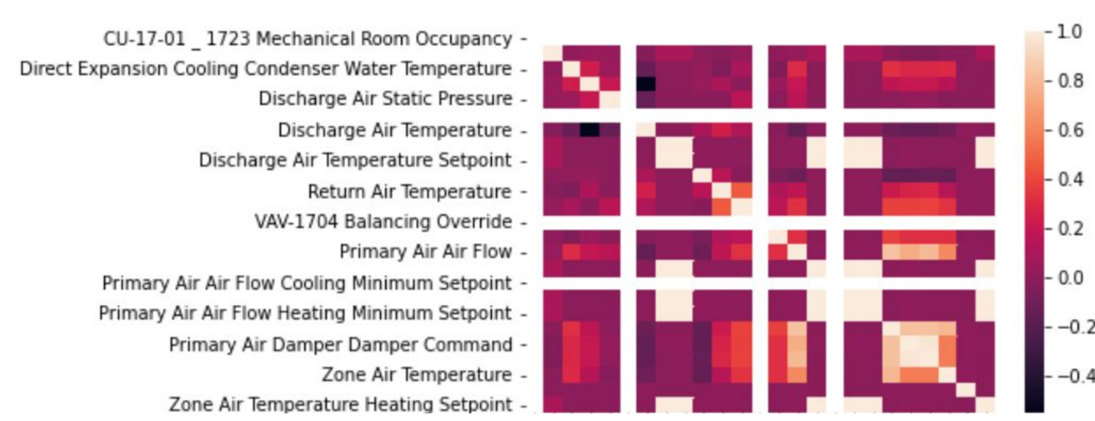

## Prediction Selection

Two variables will be predicted: ***Primary Air. Air Flow*** and ***Fin Tube Radiation.Valve Position***. Other variables were eliminated because:

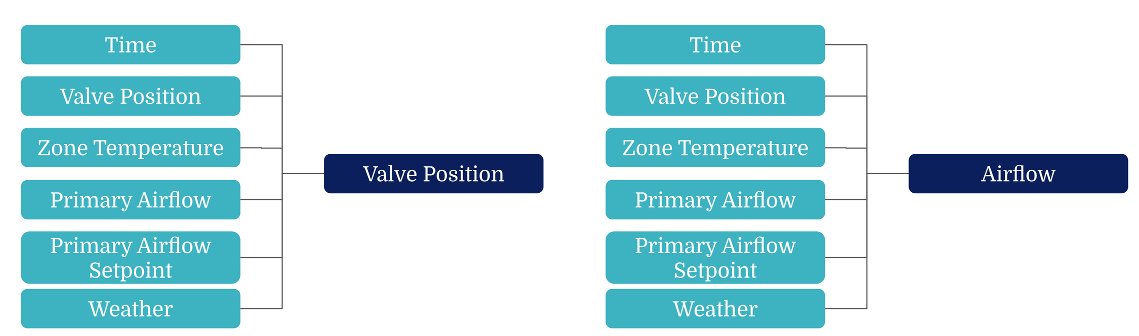
- they were setpoints
- the resolution of the dataset was too large

## Feature Selection

**Heat map of Spearman Correlation Coefficient:**




Considered the correlation coefficient and domain knowledge to determine causation relationships between the variables and develop the inputs and outputs of the valve position model (left) and airflow model (right):

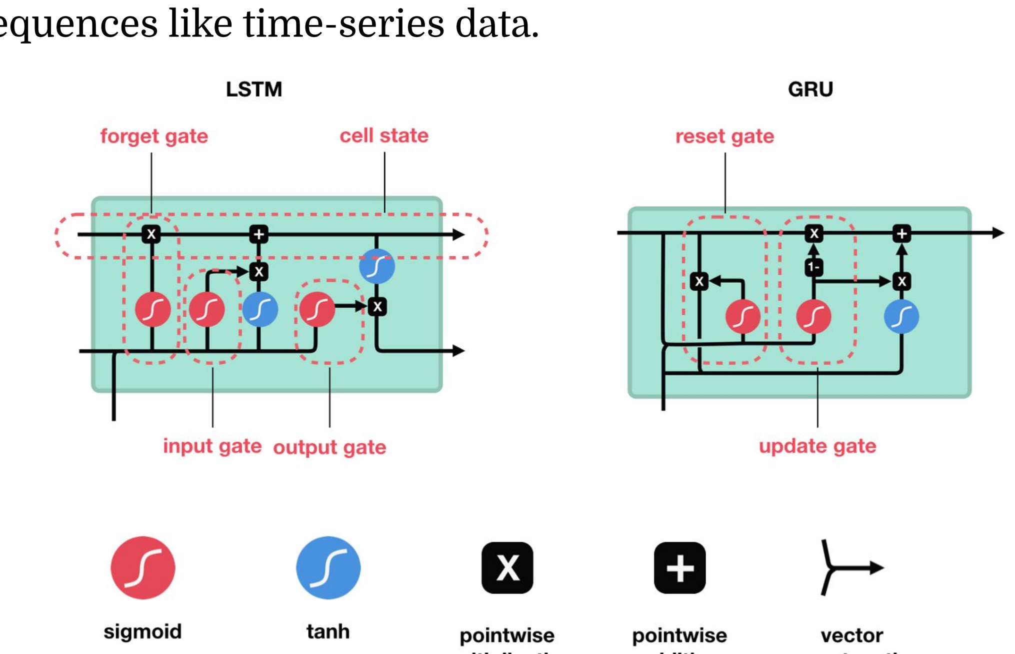



## Machine Learning Model Selection

3 models selected:

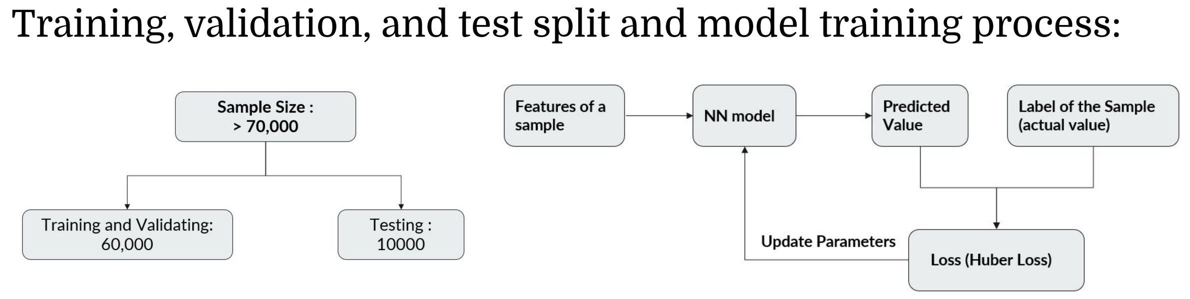
- Baseline: Vector Autoregression (Statistical method)
- LSTM (Recurrent Neural Network)
- GRU (Recurrent Neural Network)

Chain-like nature of RNNs make them suitable for use with sequences like time-series data.




## Machine Learning Workflow

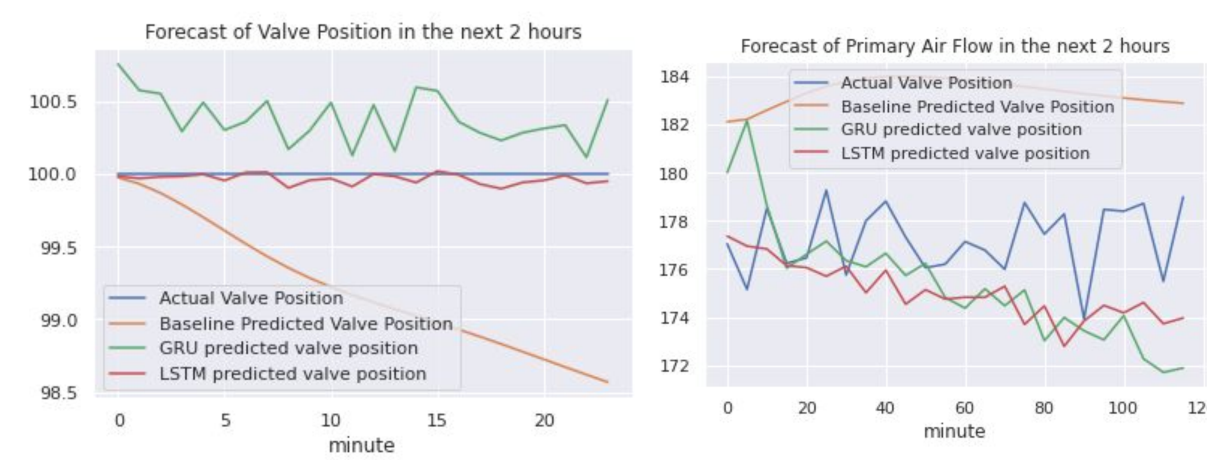
Training, validation, and test split and model training process:




## ML Results

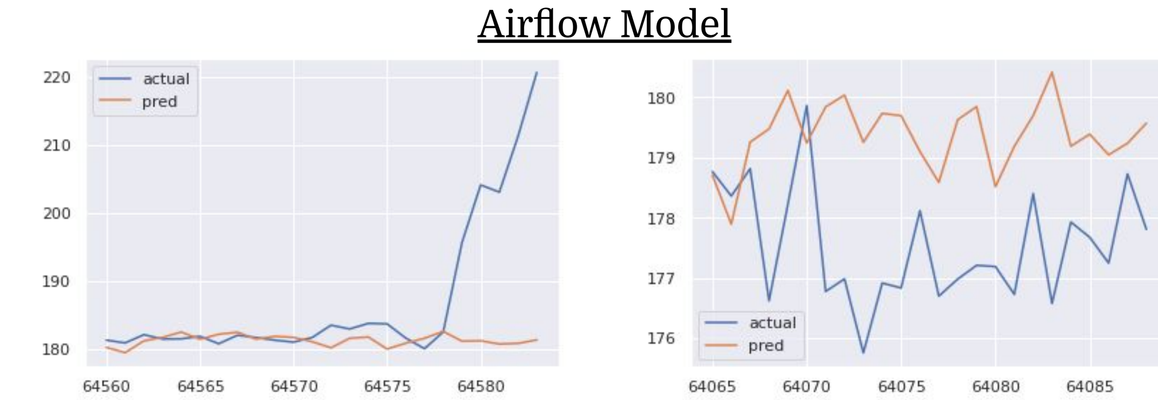
MAE achieved for each model and task:

| Model | MAE | |
|---|---|---|
| | Airflow | Valve Position |
| VAR | 23.05 | 1.32 |
| LSTM | 17.27 | 1.14 |
| GRU | 17.55 | 1.31 |




## Error Analysis

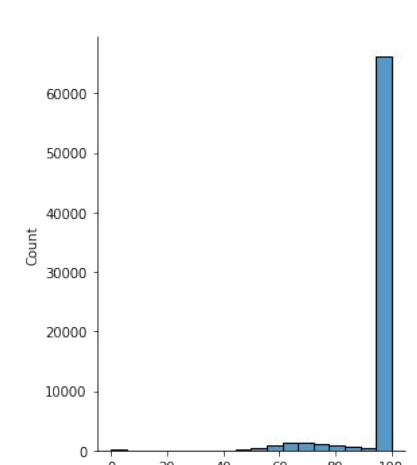
Airflow Model




Prediction failing to catch up — Overestimation

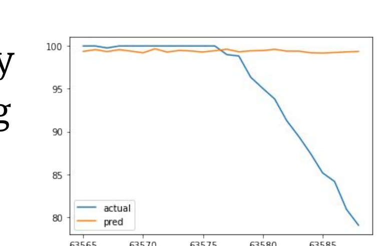

Variance — Underestimation

Valve Model

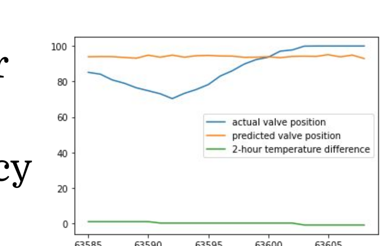


Histogram of Valve Position

- Lower accuracy when deviating from 100



- Future weather data does not improve accuracy



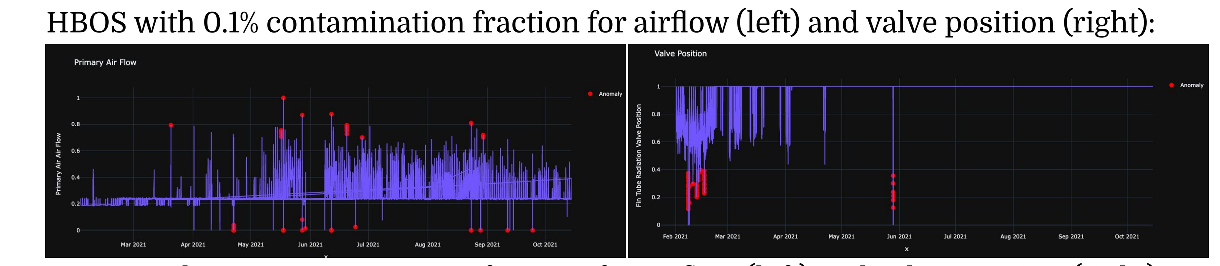
## Anomaly Detection

Due to unlabelled data, use two unsupervised anomaly detection algorithms to find global outliers and report to user.

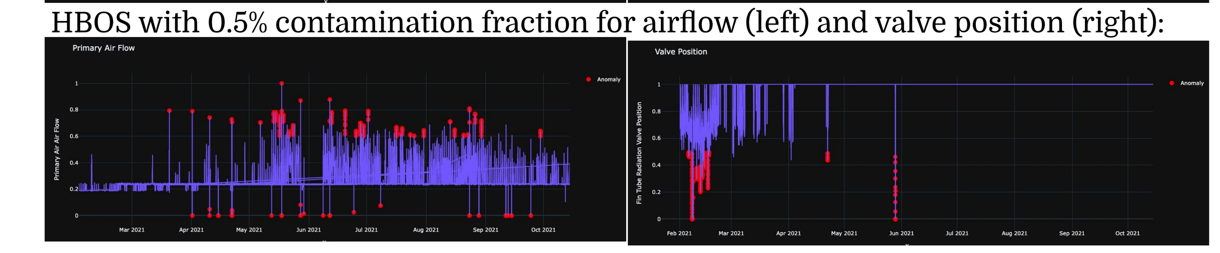
- Histogram-based Outlier Score (HBOS) is a statistical method that models the historical empirical distribution
- Isolation Forest (iForest) is a tree-based methods that isolates outliers based on average distance from the tree root

I. Number of anomalies depends on set contamination fraction

HBOS with 0.1% contamination fraction for airflow (left) and valve position (right):

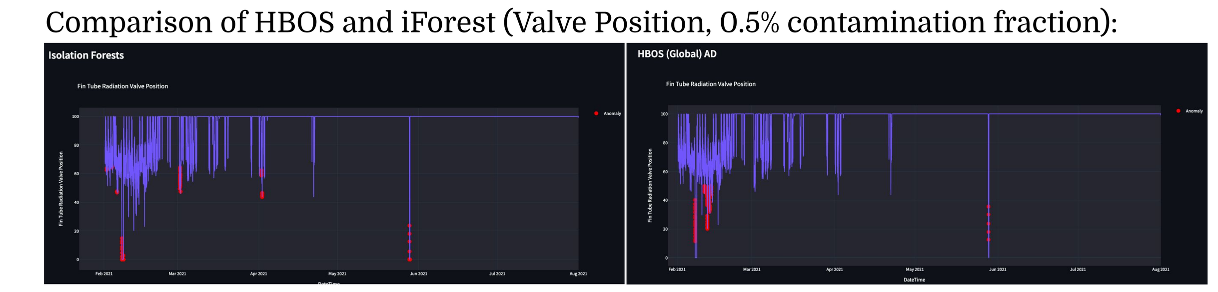


HBOS with 0.5% contamination fraction for airflow (left) and valve position (right):



II. HBOS and iForest label different points as anomalous, but without confirmed outliers, cannot make definitive judgement about algorithm performance

Comparison of HBOS and iForest (Valve Position, 0.5% contamination fraction):



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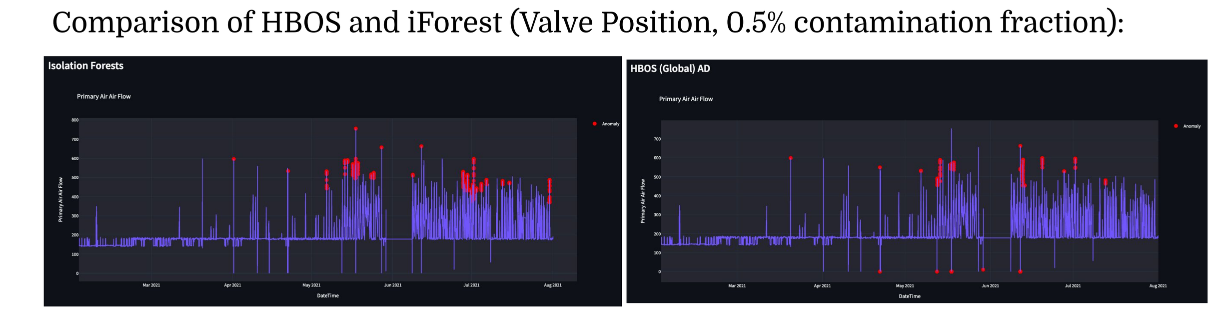
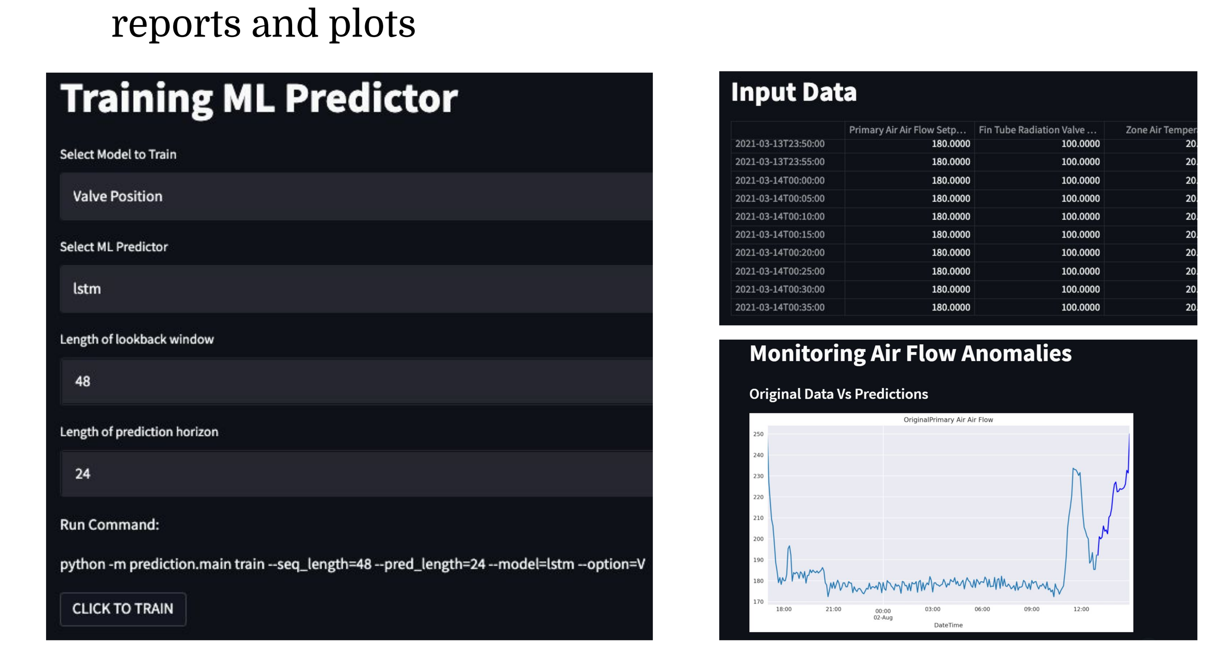


## UI Design

- User can select parameters of new GRU or LSTM to train
- User can monitor input data, new predictions and anomaly reports and plots




## Business Impact

- Satisfies MNG's goal of automating building service requests and provides centralized information and alerts.
- Reduces costly delays and downtime caused by emergency repairs.
- Makes buildings more comfortable for occupants by preventing the building parameters from entering extreme ranges.

## Next Steps

- **Improving the Dataset:** Adding more time-series data and documenting service calls that align with sensor data.
- **Improving the Machine Learning Model:** Further tuning of PoC and modelling for further accuracy and reliability.
- **Expanding the Diversity of Predictions:** Develop more models and identify more inputs & outputs.