Modern Niagara Group

Intelligent Predictive Building System Maintenance Integration Platform

APS490 Multidisciplinary Capstone Design Review & Critique
Jan. 13th, 2022

Capstone Design Team

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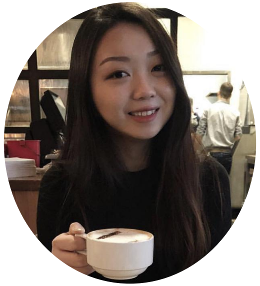

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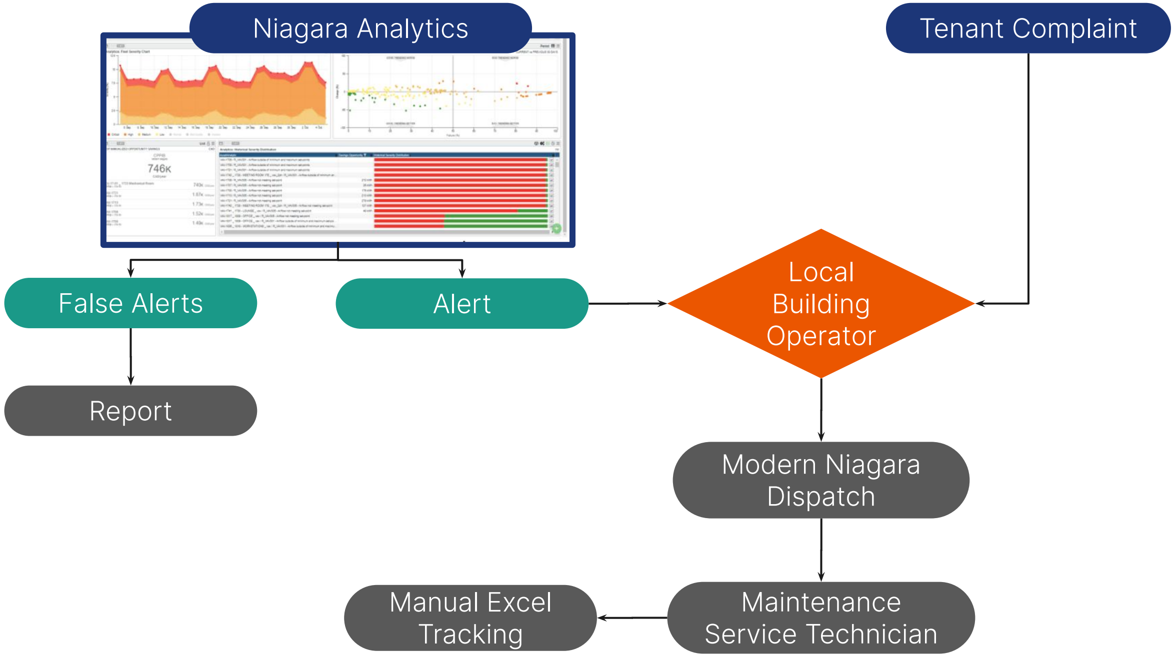
Faculty of Information

Summary

Problem, Scope, Objective

Problem

For maintenance issues (i.e. abrupt faults and degradation faults), MNG is reliant on local building operators to recognize issues and place a call to MNG’s 24/7 dispatch.



Agenda

1. Brief Introduction: Problem Statement, Scope, Objective
2. Digital Twin Overview
3. Amendment to Design Proposal
4. ML Design Justification
5. Model Results and Comparison
6. Anomaly Detection
7. Validation / Verification of Design Against Requirements
8. Next Steps
9. Work Plan

Scope

Predicting these emergency maintenance events ahead of time, while the fault is in the early stage.

Objective

Develop a proof-of-concept that can identifying potential failures before they occur, without manual intervention.

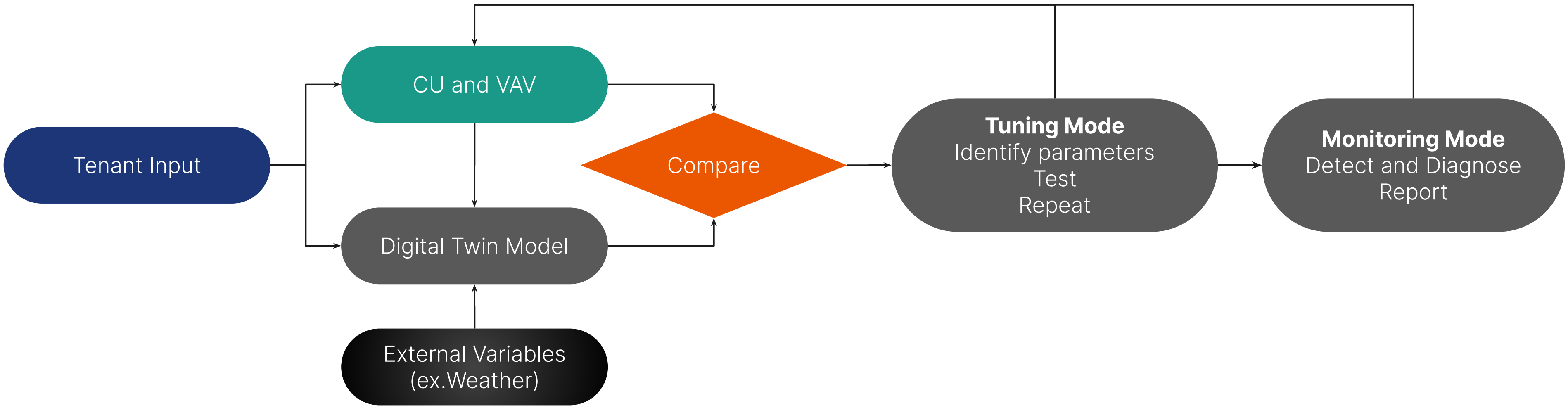
17th Floor of Canadian Pension Plan Investment Board (CPPIB) building.

Air Handling Central Unit (CU) and Variable Air Volume (VAV) system

2.Mechanism

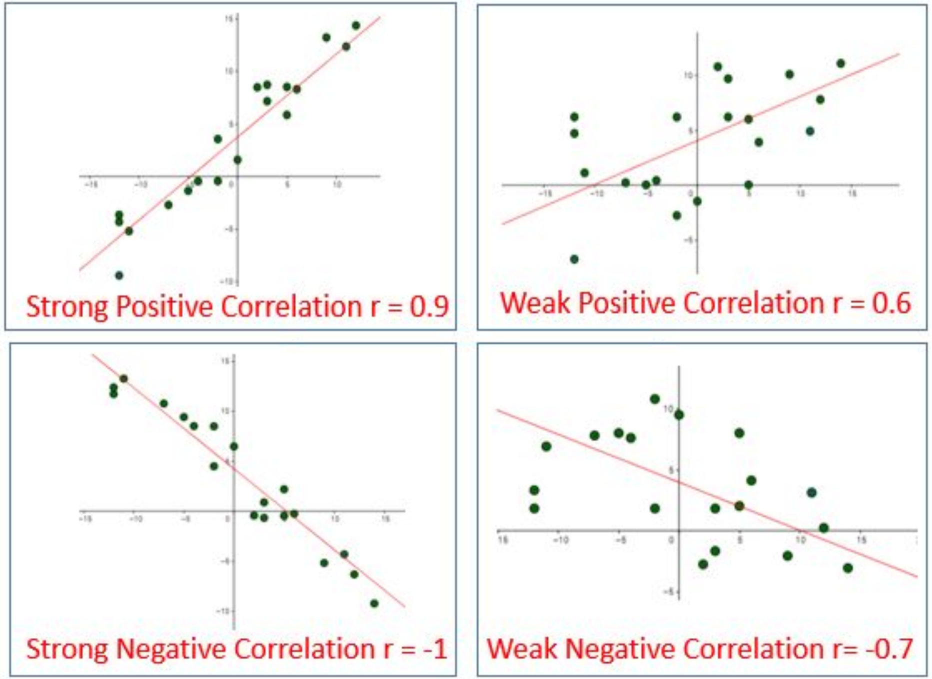
Digital Twin

Diagram of the Digital Twin

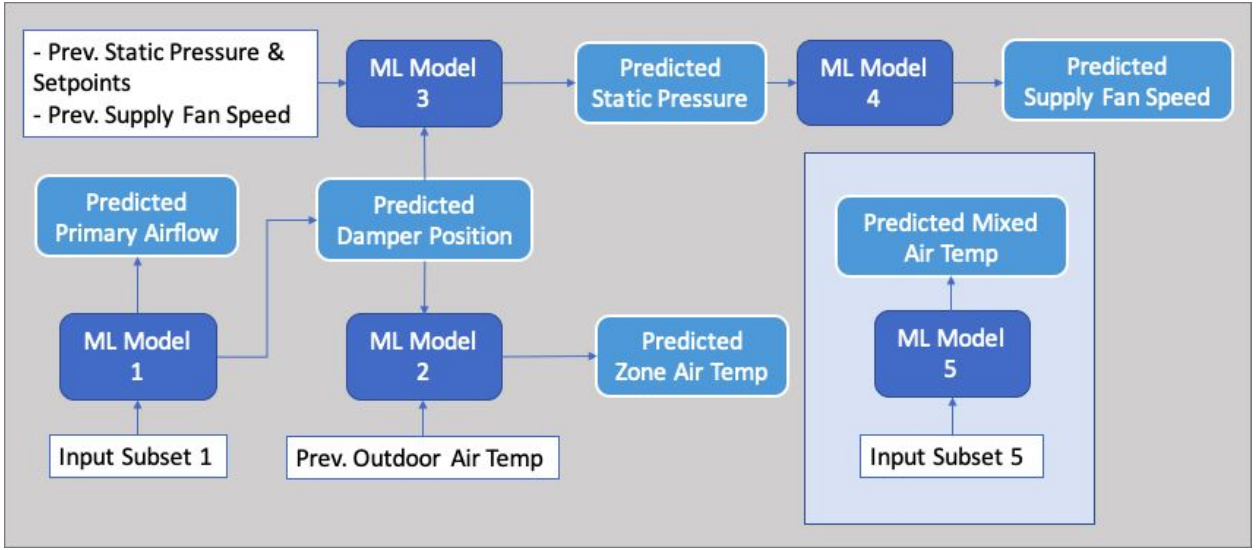


3. Amendments to Design Proposal

Spearman Correlation Coefficient

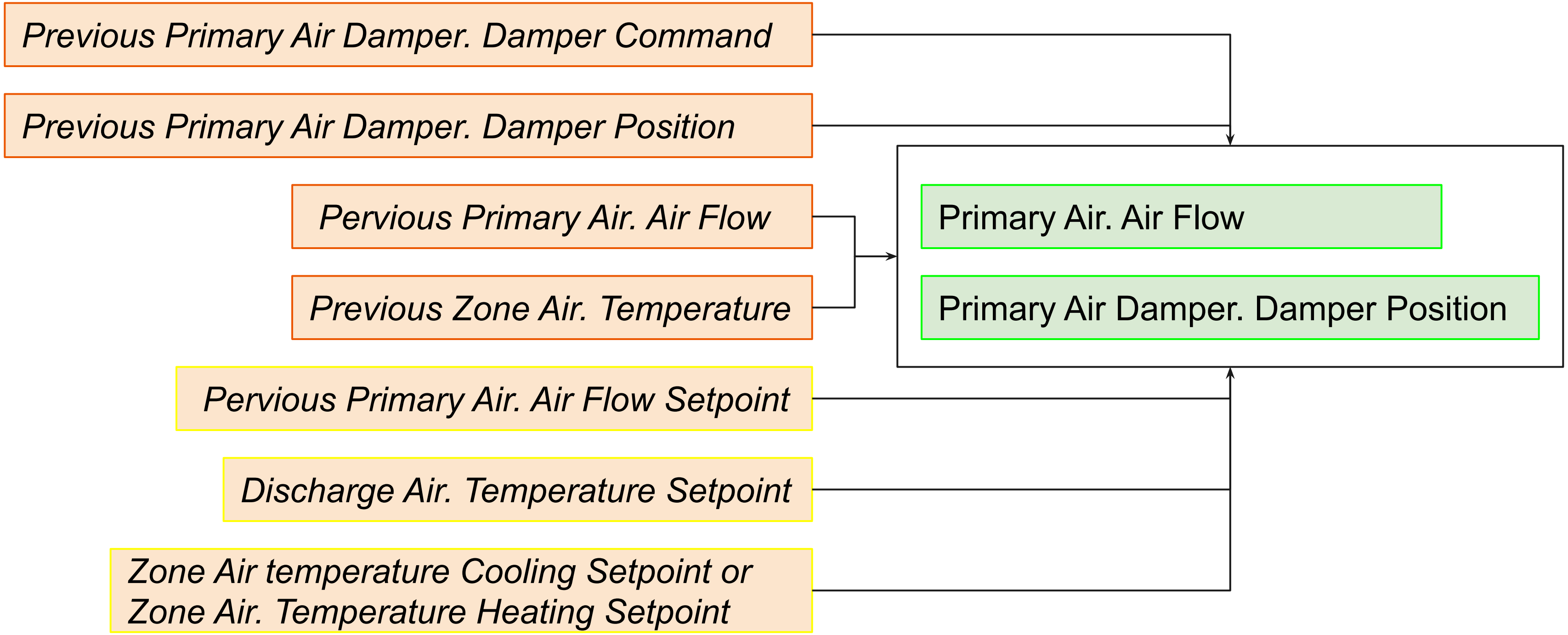


Design Proposed in Design Proposal (Nov 2021)

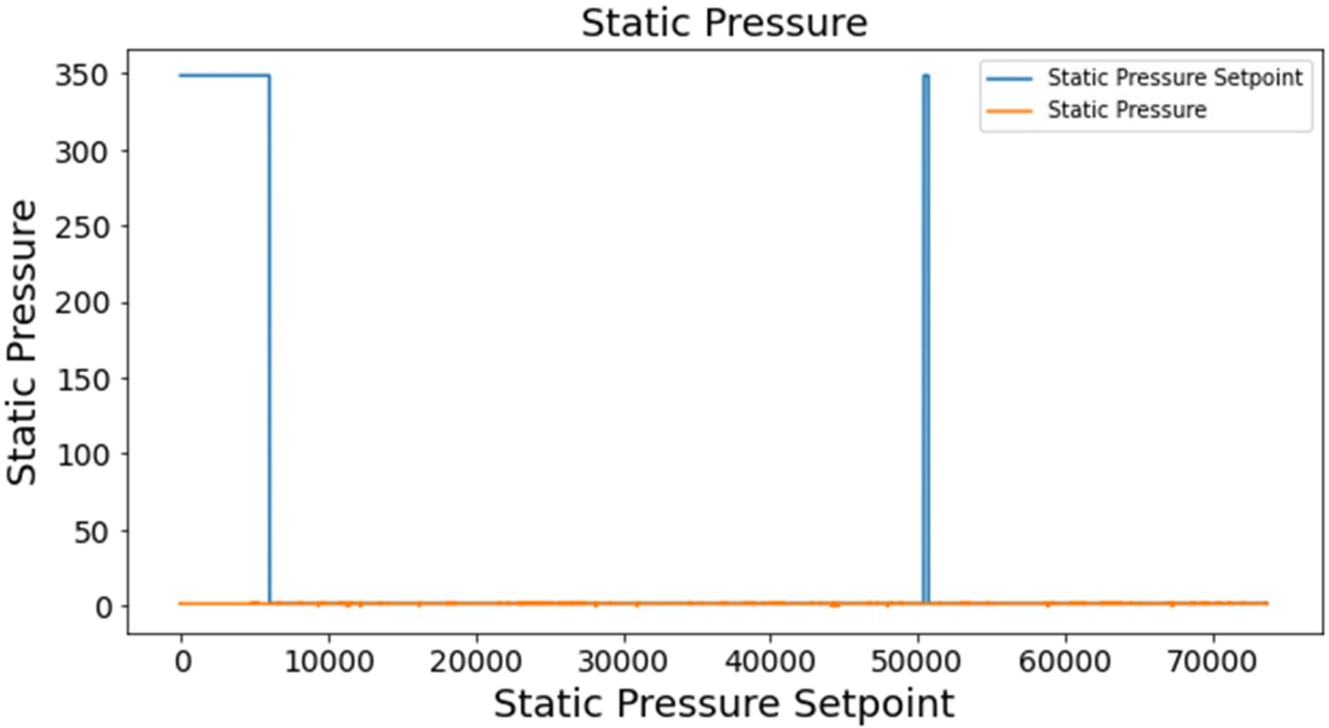


Alternative Design #2: Deep Regressor Chain

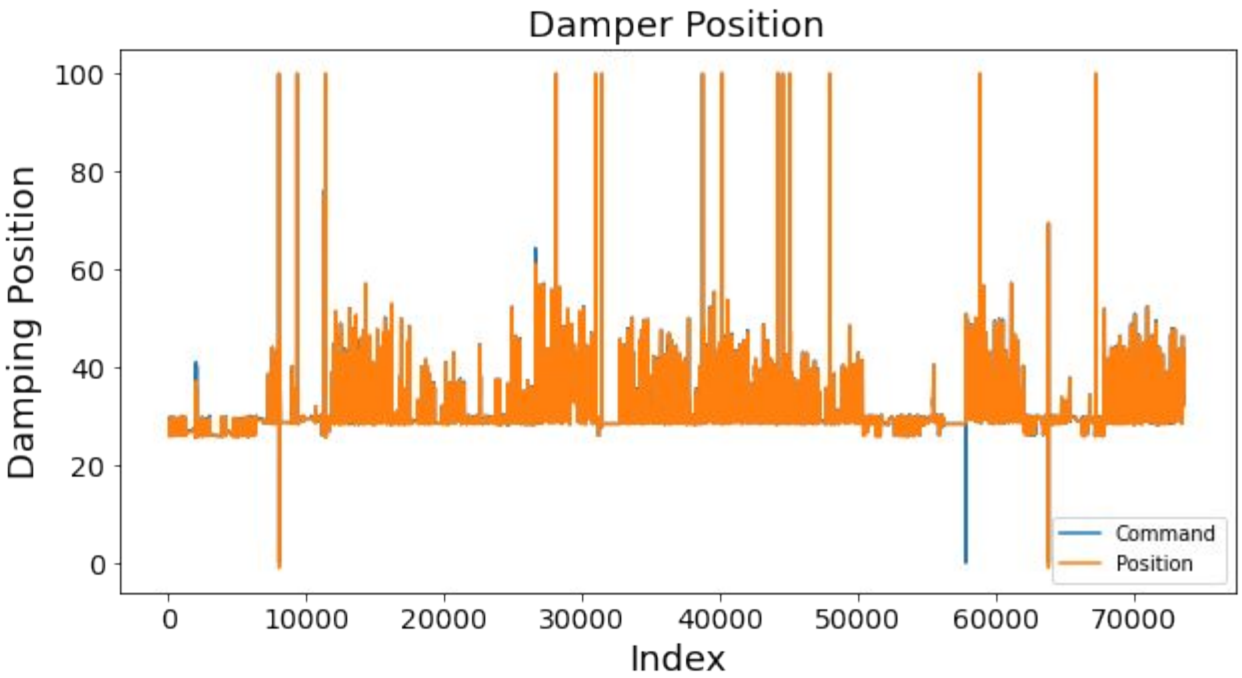
Proposed Model 1: Airflow / Damper Position



Proposed Model 1: Airflow / Damper Position

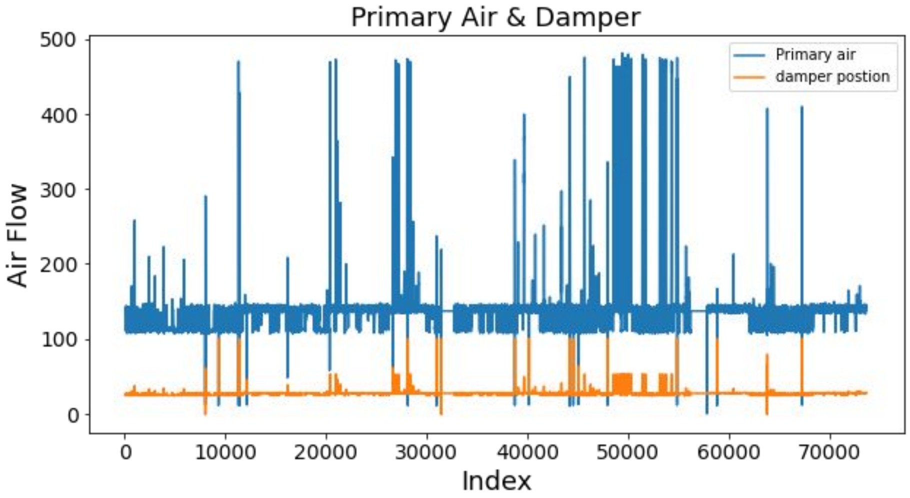


Proposed Model 1: Airflow / Damper Position



Airflow and Damper Position

- Damper position directly controls airflow, which is why it is excluded from the inputs

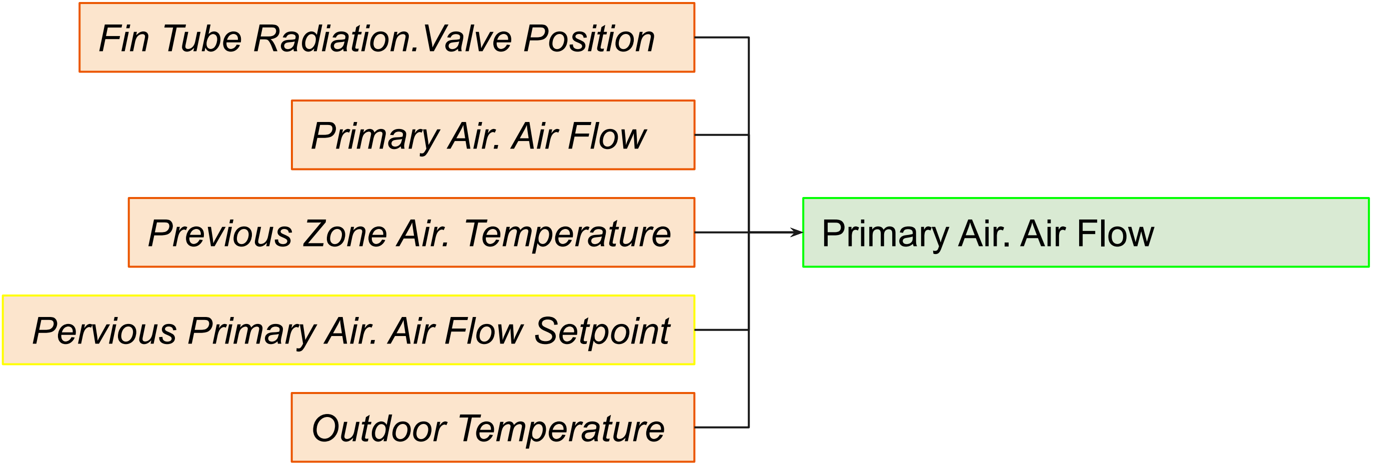


Correlation Coefficients for Airflow

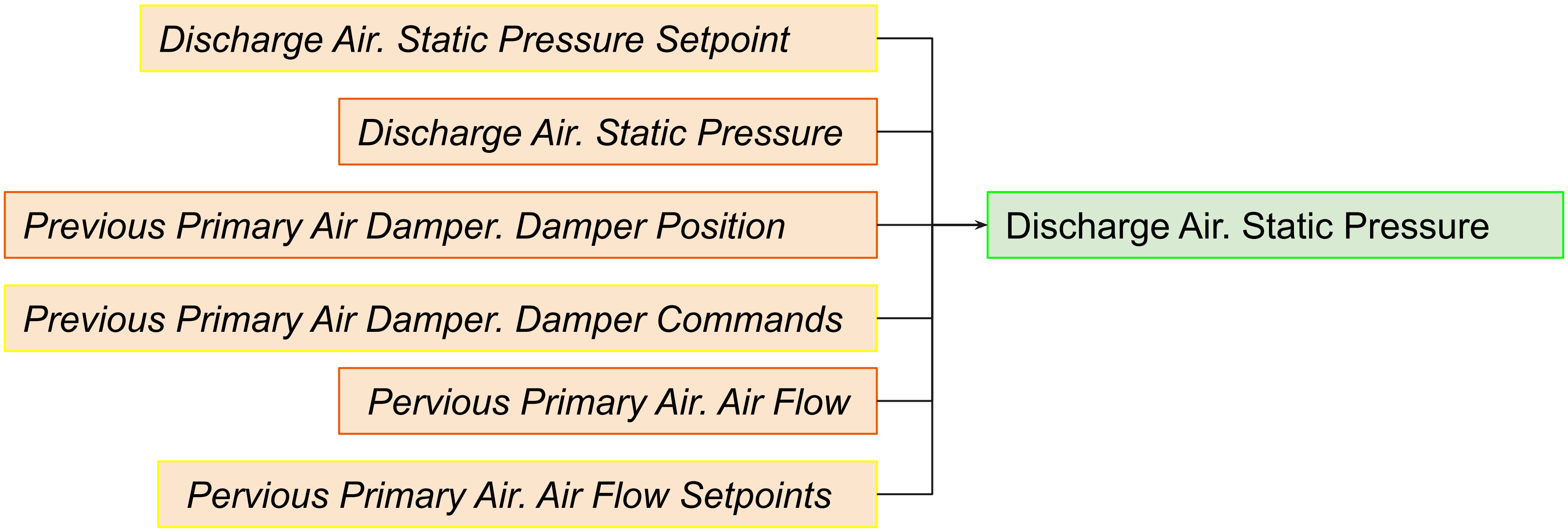
	Condenser Water Temp	Cooling Capacity	Return Air.Temp	Supply Fan.Speed	**Valve Position**	Air Flow	**Air Flow Setpoint**	Damper Command	Damper Position	**Zone Air.Temp**
Air Flow	0.3038	0.1944	0.1816	0.3294	**0.3260**	1	**0.8335**	0.7507	0.7982	**0.6225**

- Static pressure in the main duct indicates whether airflow should be behaving normally
- Some coefficients merely show correlation, while causality is what we ideally need to construct a model for fault detection and diagnosis

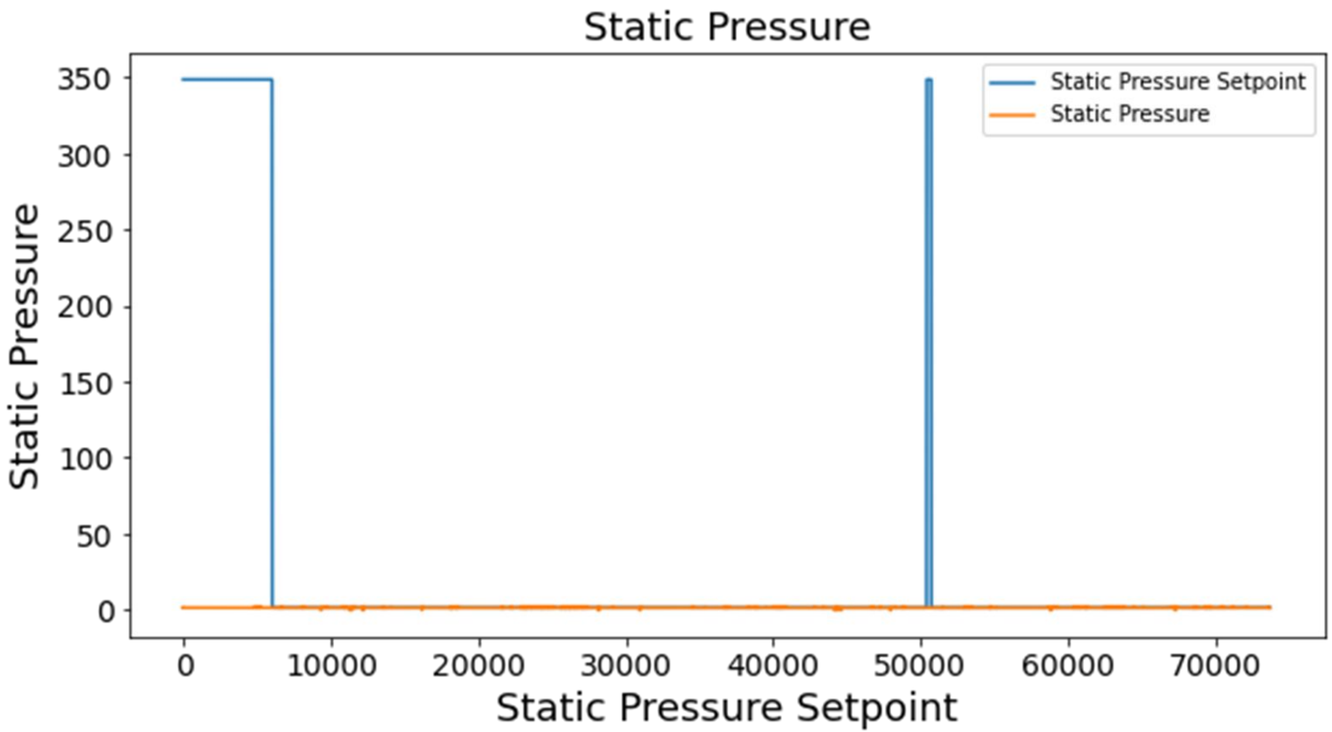
Revised Model 1: Airflow



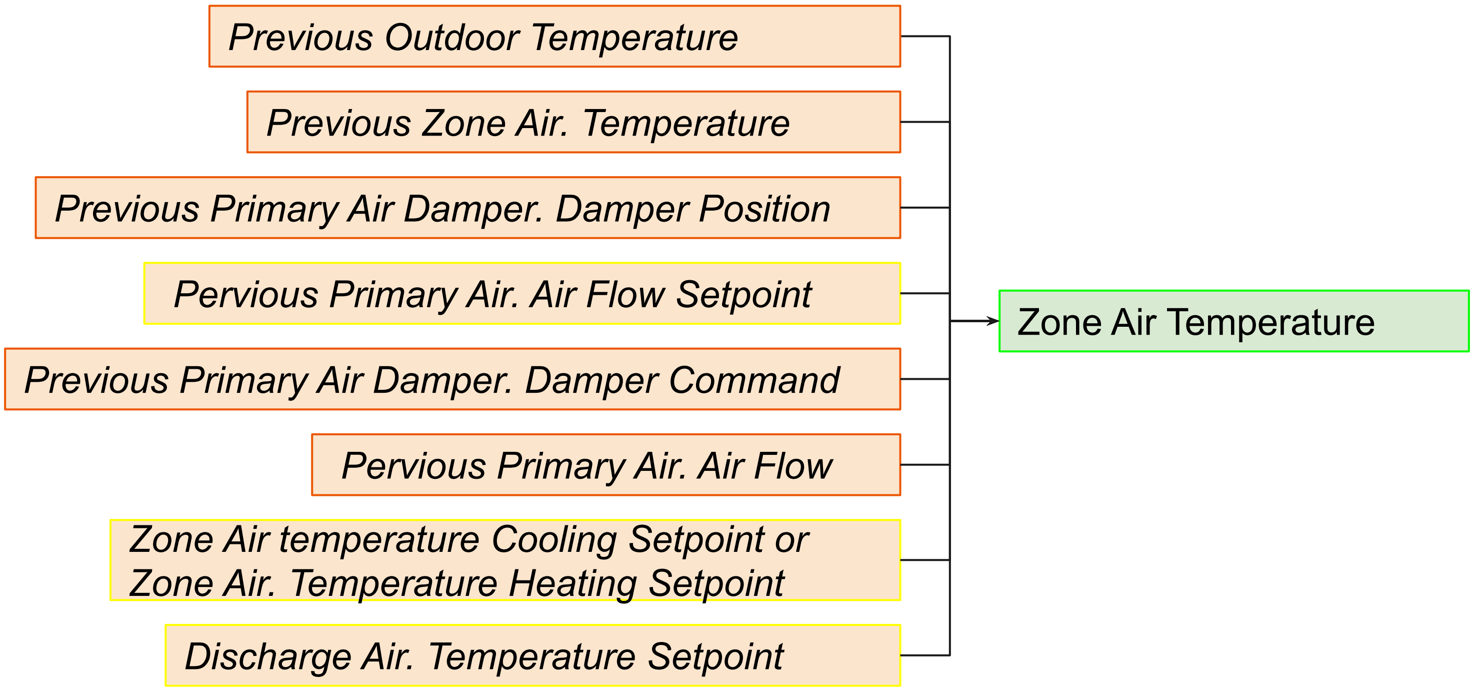
Proposed Model 2: Static Pressure Prediction



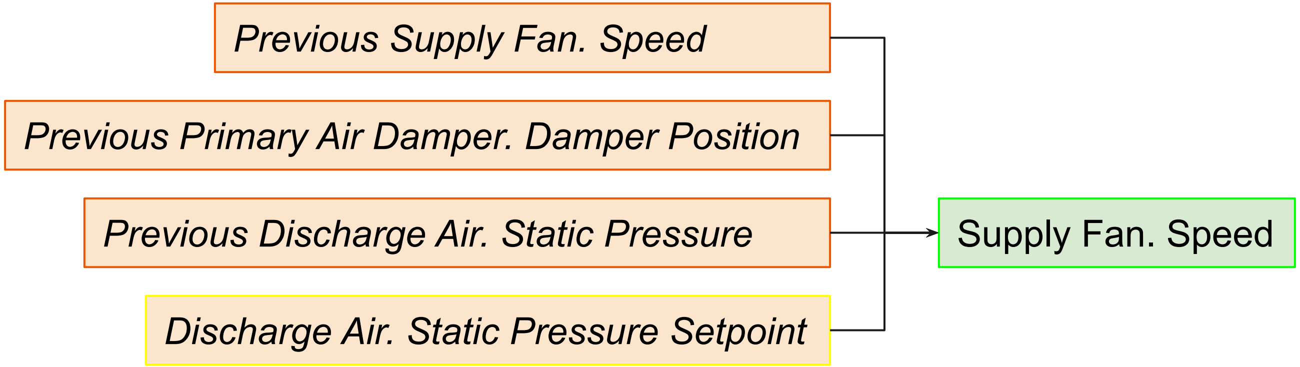
Proposed Model 2: Static Pressure Prediction



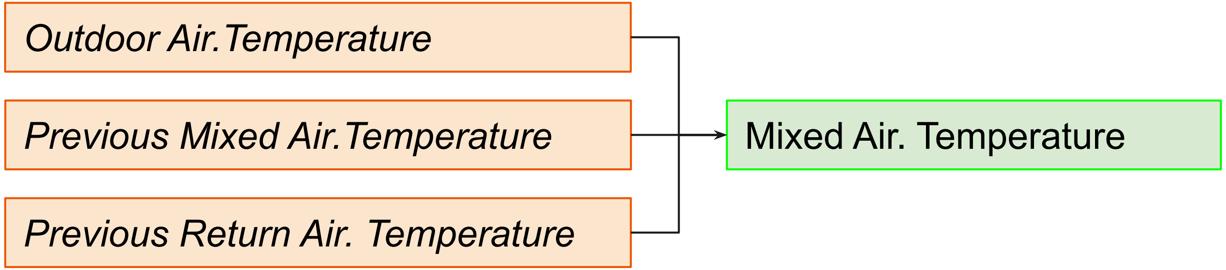
Proposed Model 3: Zone Air Temperature



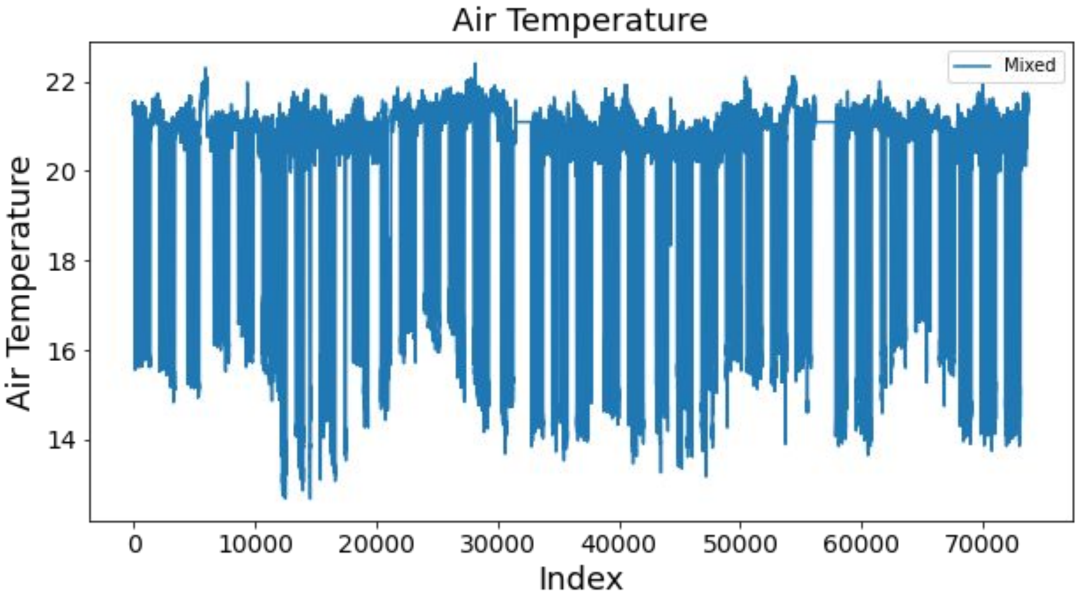
Proposed Model 4: Supply Fan Speed



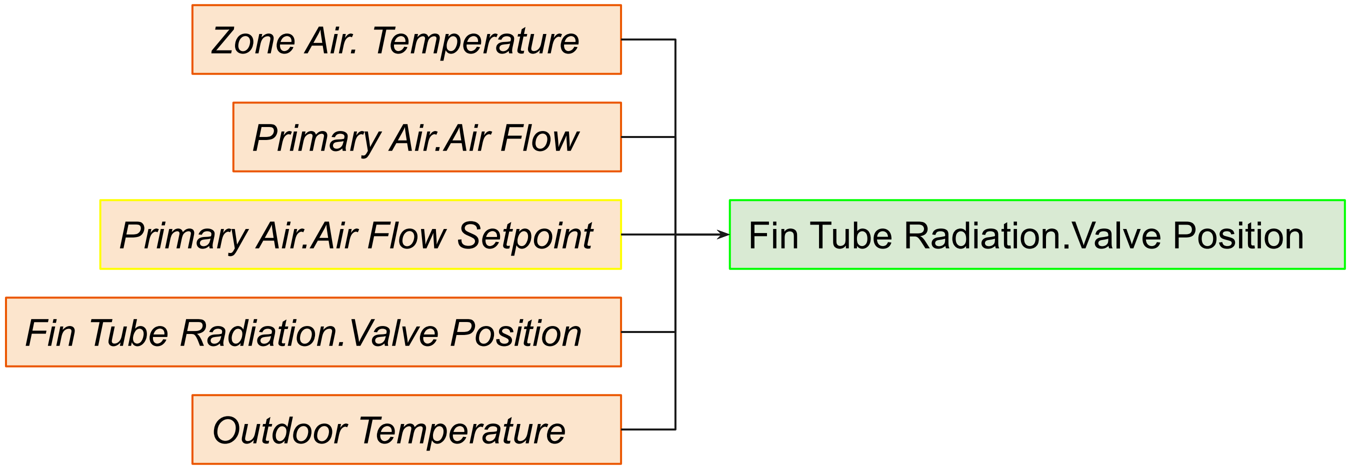
Proposed Model 5: Mixed Air Temperature



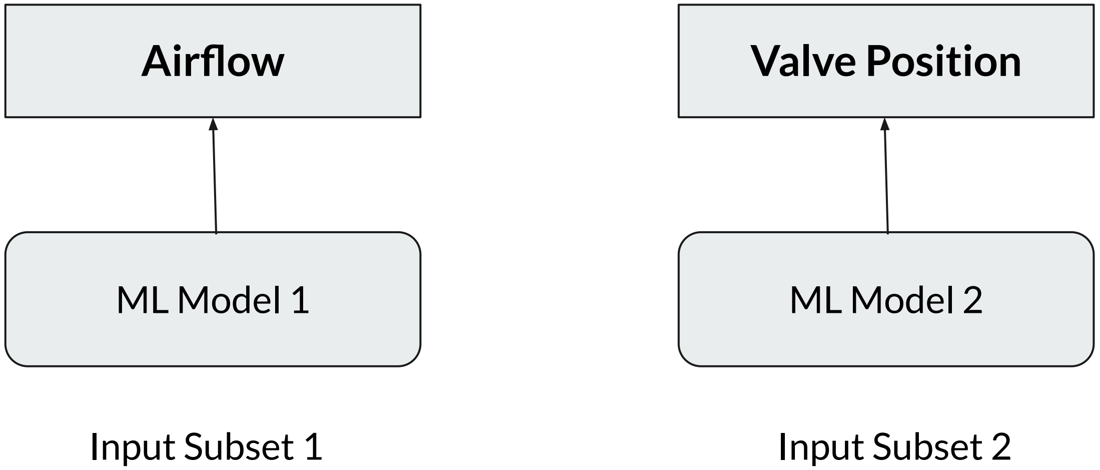
Proposed Model 5: Mixed Air Temperature



New model: Fin Tube Valve Position



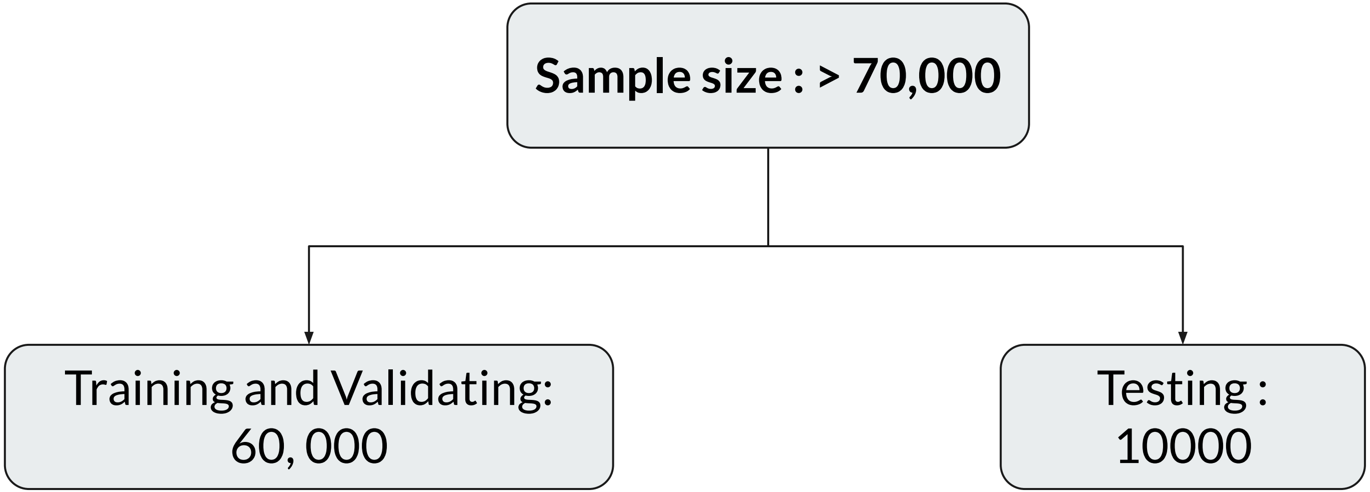
Current Design



4. Model Architecture Selection

Model architectures for prediction: Baseline (VAR), LSTM, and GRU

Datasets


Sample size : > 70,000
Training and Validating:
60, 000
Testing :
10000

Baseline Model: Vector Autoregression (VAR)

Vector autoregression (**VAR**) is a statistical model used to capture the relationship between multiple quantities as they change over time.

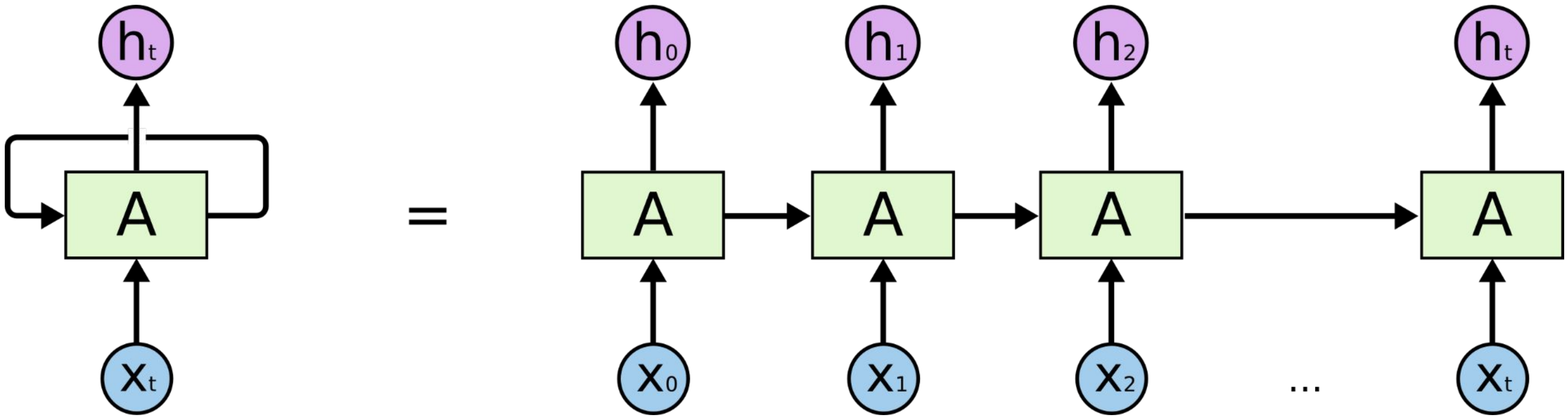
- Typically used for multivariate time-series forecasting
- Appropriate for variables that move together in time (cointegrated) in a stationary manner

$$
\begin{aligned}
Y_t &= \alpha + \beta_{11} Y_{t-1} + \beta_{12} Y_{t-2} \\
&\quad + \gamma_{11} X_{t-1} + \gamma_{12} X_{t-2} + \varepsilon_{1t} \\
X_t &= \alpha_2 + \beta_{21} Y_{t-1} + \beta_{22} Y_{t-2} \\
&\quad + \gamma_{21} X_{t-1} + \gamma_{22} X_{t-2} + \varepsilon_{2t}
\end{aligned}
\tag{1}
$$

Formula for two variable VAR with a two-step lag

Chris Sims. Macroeconomics and Reality, Econometrica. 1980.

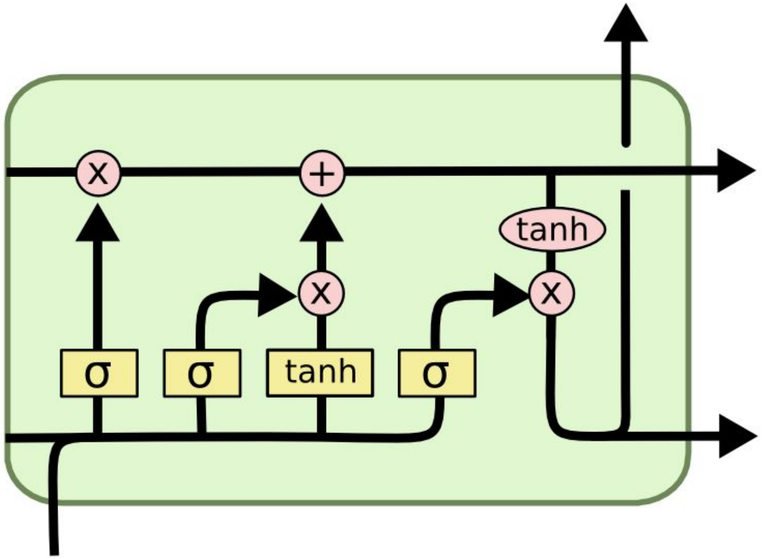
Recurrent Neural Networks (RNNs)



A RNN is suitable for our problem as it has “loops” that allow information to persist (unlike in other tradition neural networks). This chain-like nature makes RNNs suitable for use with sequences - like our time-series data.

Model 1: Long Short-Term Memory (LSTM)

Long Short-Term Memory is a type of RNN that is capable of learning the long-term dependencies between variables.

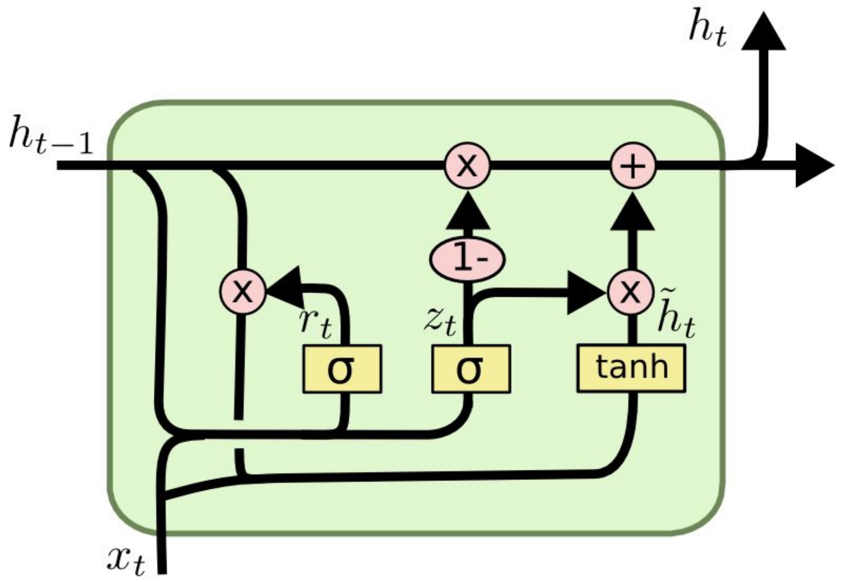


Sepp Hochreiter. Long short-term Memory. 1997.

Model 2: Gated-Recurrent Unit (GRU)

Gated-Recurrent Unit (GRU) is a type of RNN that is similar to LSTM.

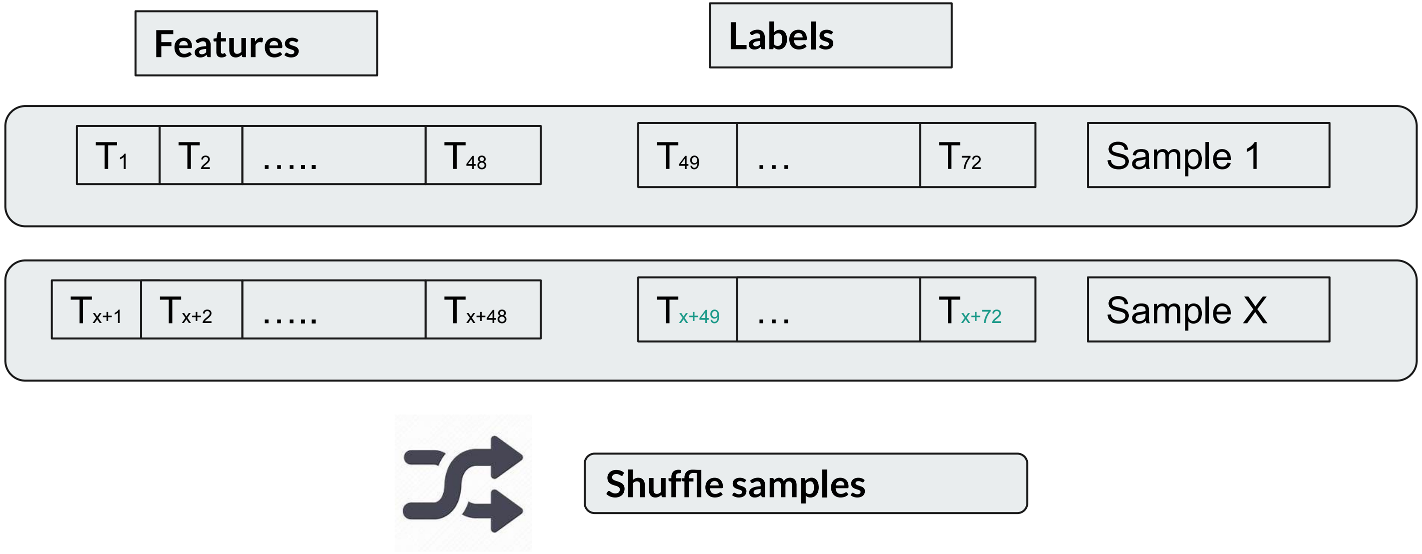
- The GRU model has a slight difference in model architecture, helps solving Vanishing Gradients issue *(In our case, 0 in datasets might cause the problem).*



K. Cho, D. Bahdanau, F. Bougares, H. Schwenk & Y. Bengio. Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation. 2014.

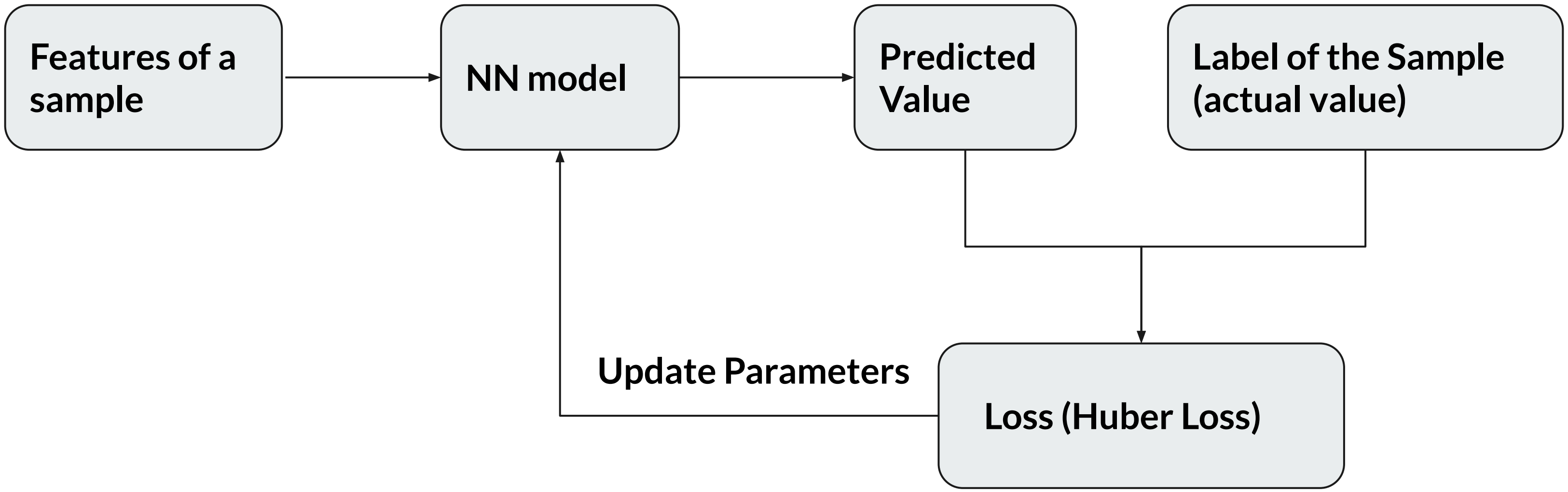
Supervised learning

1. **Build Samples**



Supervised learning

2. Feeding samples to NN model



5. Model Results

Model architecture, Detection methods

Evaluating the Performance

MAE (Mean Absolute Error)

MAPE (Mean Absolute Percentage Error)

$$MAE = \frac{1}{n}\sum_t |A_t - F_t|$$
$$MAPE = \frac{1}{n}\sum_t \left|\frac{A_t - F_t}{A_t}\right|$$

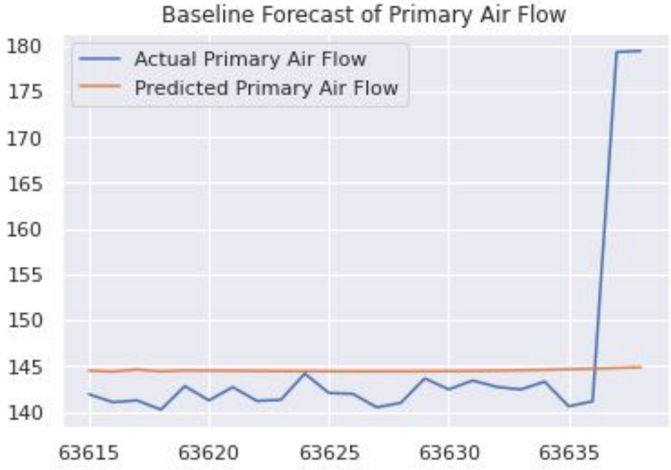
where A_t is actual value at time t
and F_t : forecasted value at time t

Method 1: Vector AutoRegression (VAR)

Air flow Prediction

TEST MAE: 23.24
TEST MAPE: 9.76%

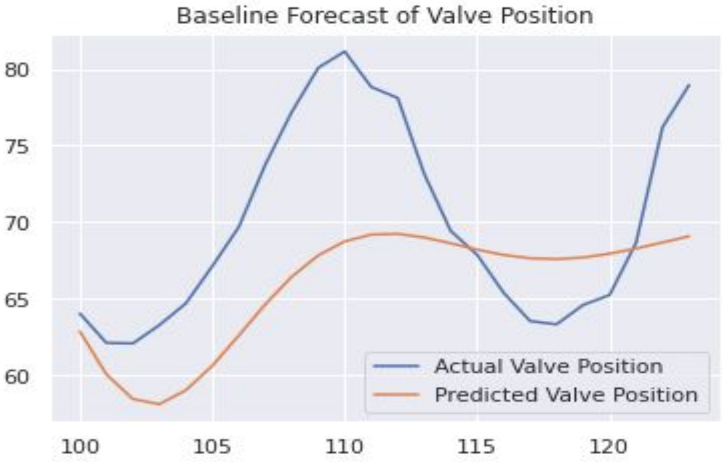
Sample



Valve Position Prediction

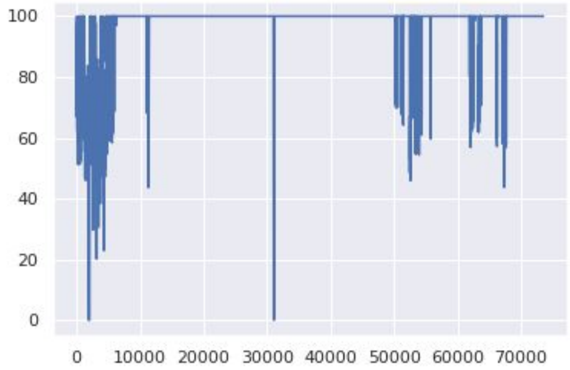
TEST MAE: 1.32
TEST MAPE: 1.50%

Sample



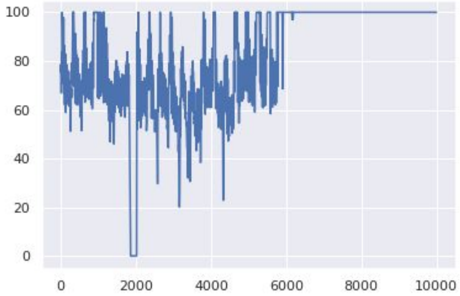
Limitation: Vector AutoRegression (VAR) is not robust

Range of Valve positions value (0 - 100)



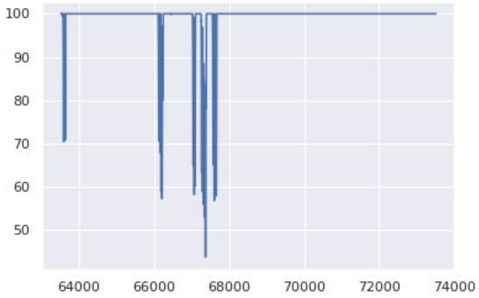
**Note: across 9 months; timestamps interval is 5 min

Testing data



MAE: 3.47

MAPE: 3.61%



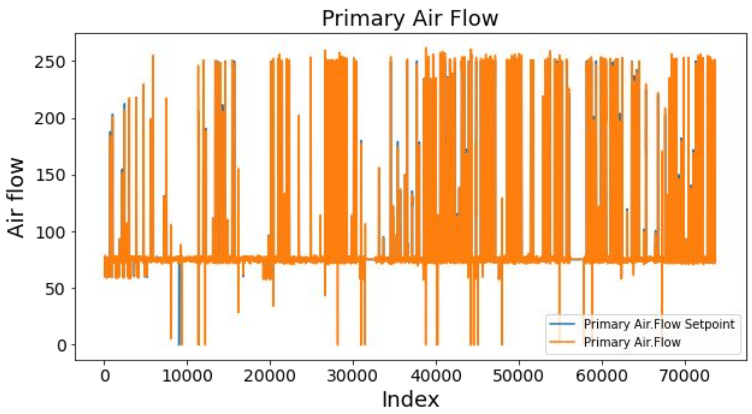
MAE: 1.32

MAPE: 1.50%

Extension: method 2 Neural Network Model

Air flow Prediction results

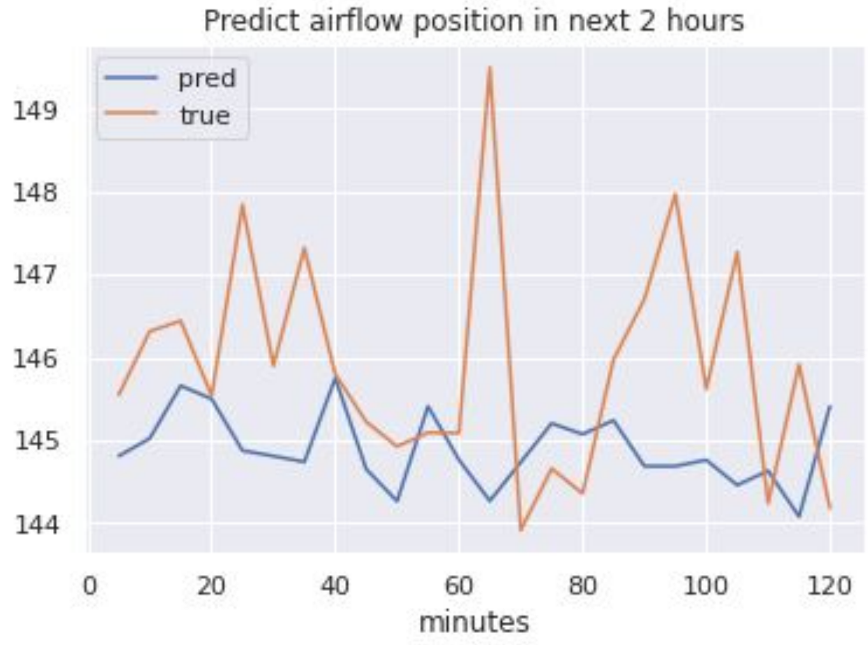
Range of air flow value (0 - 250)



	MAE	MAPE
VAR	23.25	9.76%
LSTM	17.06	6.82%
GRU	16.84	6.74%

Air Flow Prediction Samples

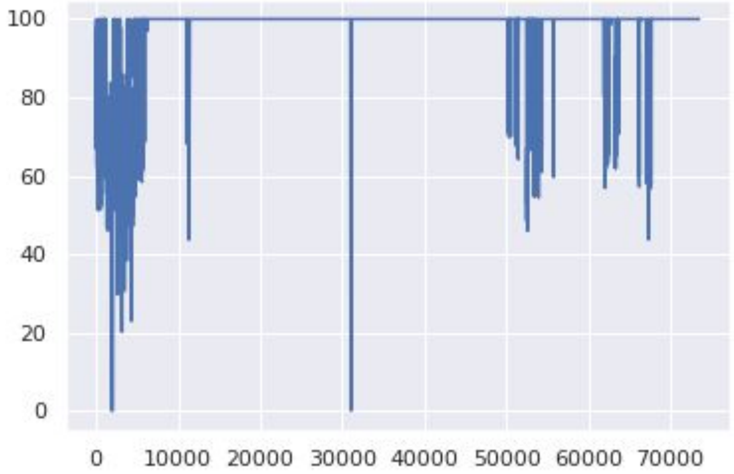
Sample 1



Extension: method 2 Neural Network Model

Valve Position Prediction Results

Range of Valve positions value (0 - 100)



	MAE	MAPE
VAR	1.32	1.50%
LSTM	1.13	1.18%
GRU	1.14	1.57%

Valve Position Prediction Samples

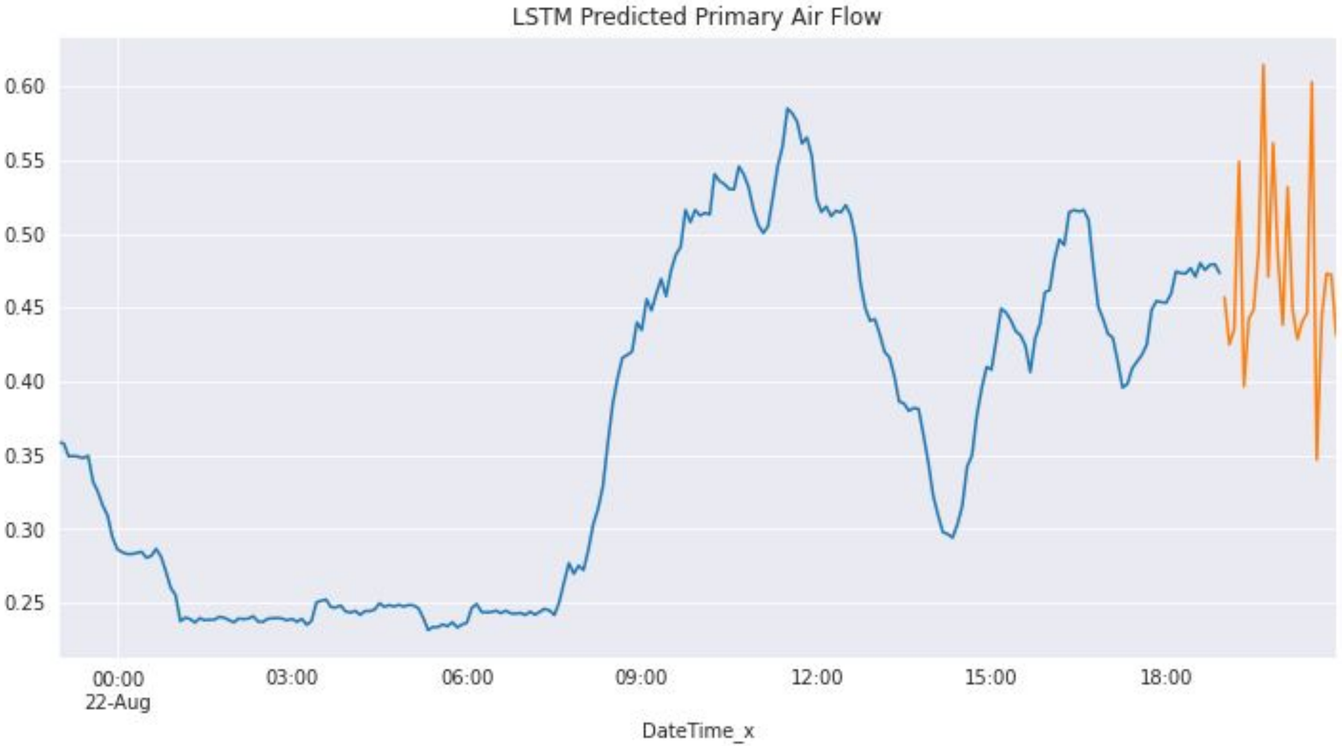
Sample 1

Sample 2

5.Anomaly Detection

STEP 1: Predict Future Values
STEP 2: Monitor for Anomalies

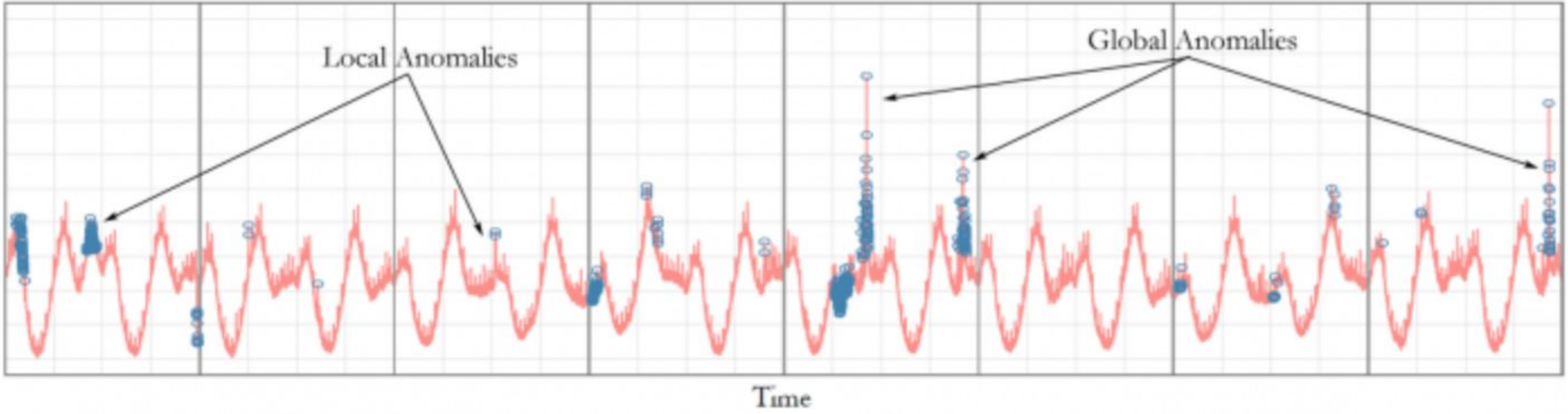
1. Use prediction module to predict next 2hrs

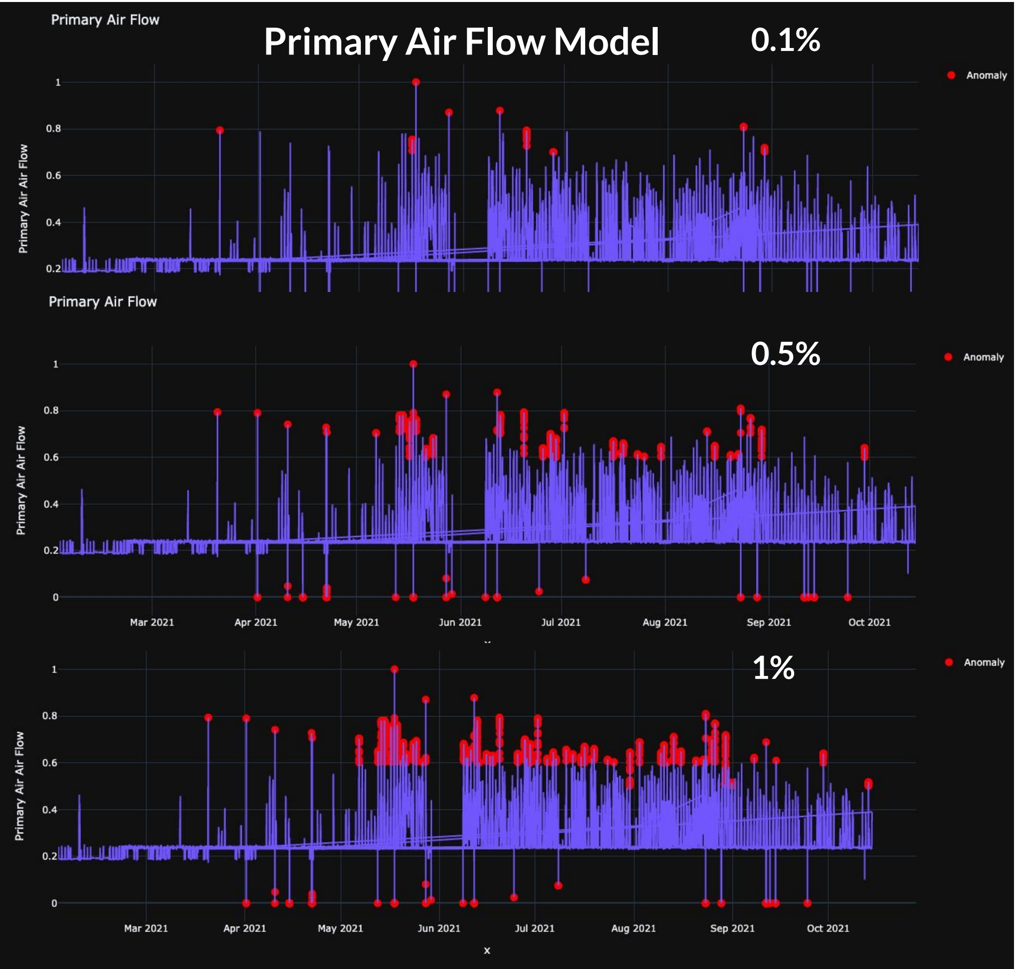


Actual Primary Air flow (Blue) vs 2-hour forecast (Orange)

2. Histogram-based Outlier Score (HBOS)

- Unsupervised distance-based outlier-selection algorithm that evaluates the frequency of occurrence of a data point
- Is a global rather than a local outlier selection method





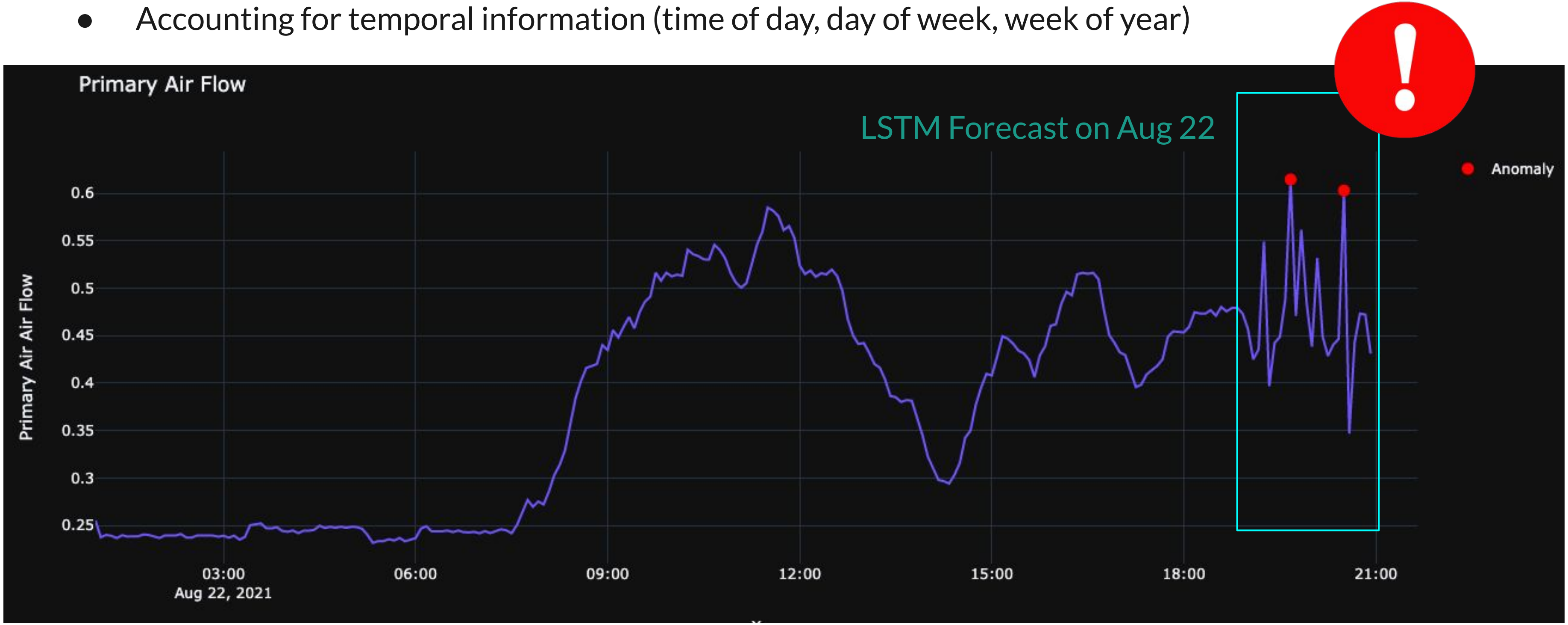
Fraction of Contamination

- Without labelled anomaly data, we assume a fraction of the input data contains outliers (contamination)

- The sensitivity of the model depends on the fraction

Anomaly Detection in Practice

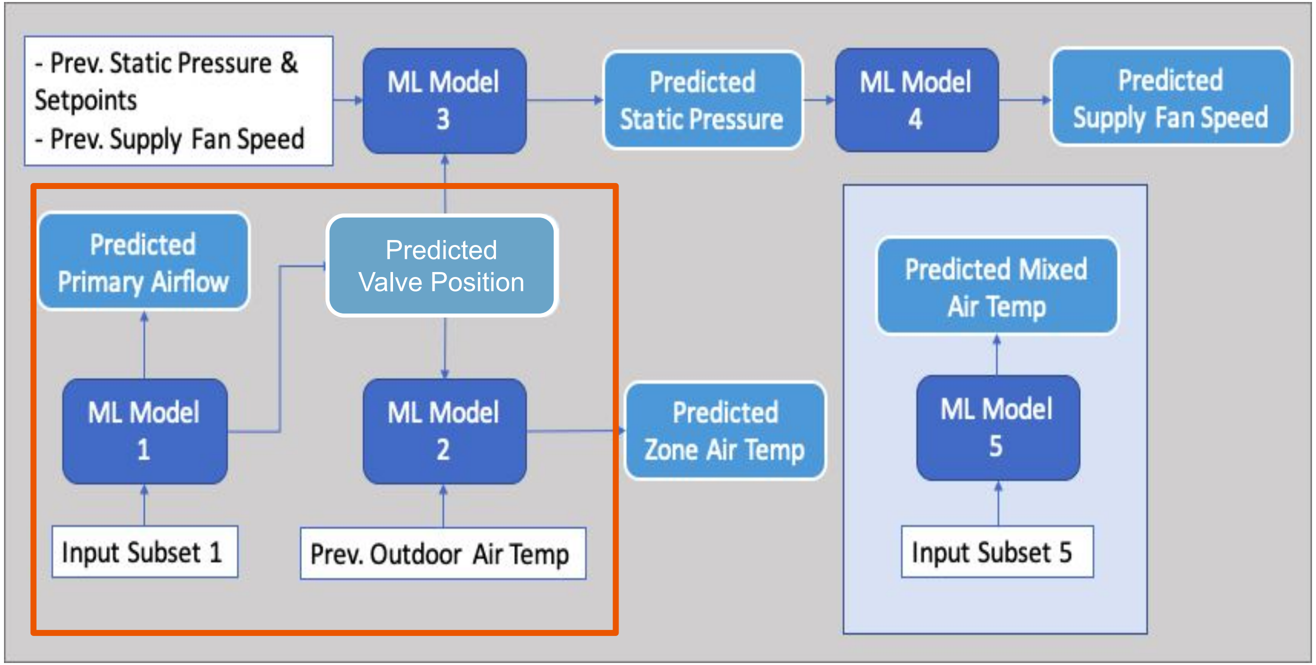
- Accounting for temporal information (time of day, day of week, week of year)



6.Next Steps

- Implement Deep Regressor Chains
- Further optimize inputs & outputs
- Tune Anomaly Detector
- Build ML Pipeline

Deep Regressor Chains (DRC)

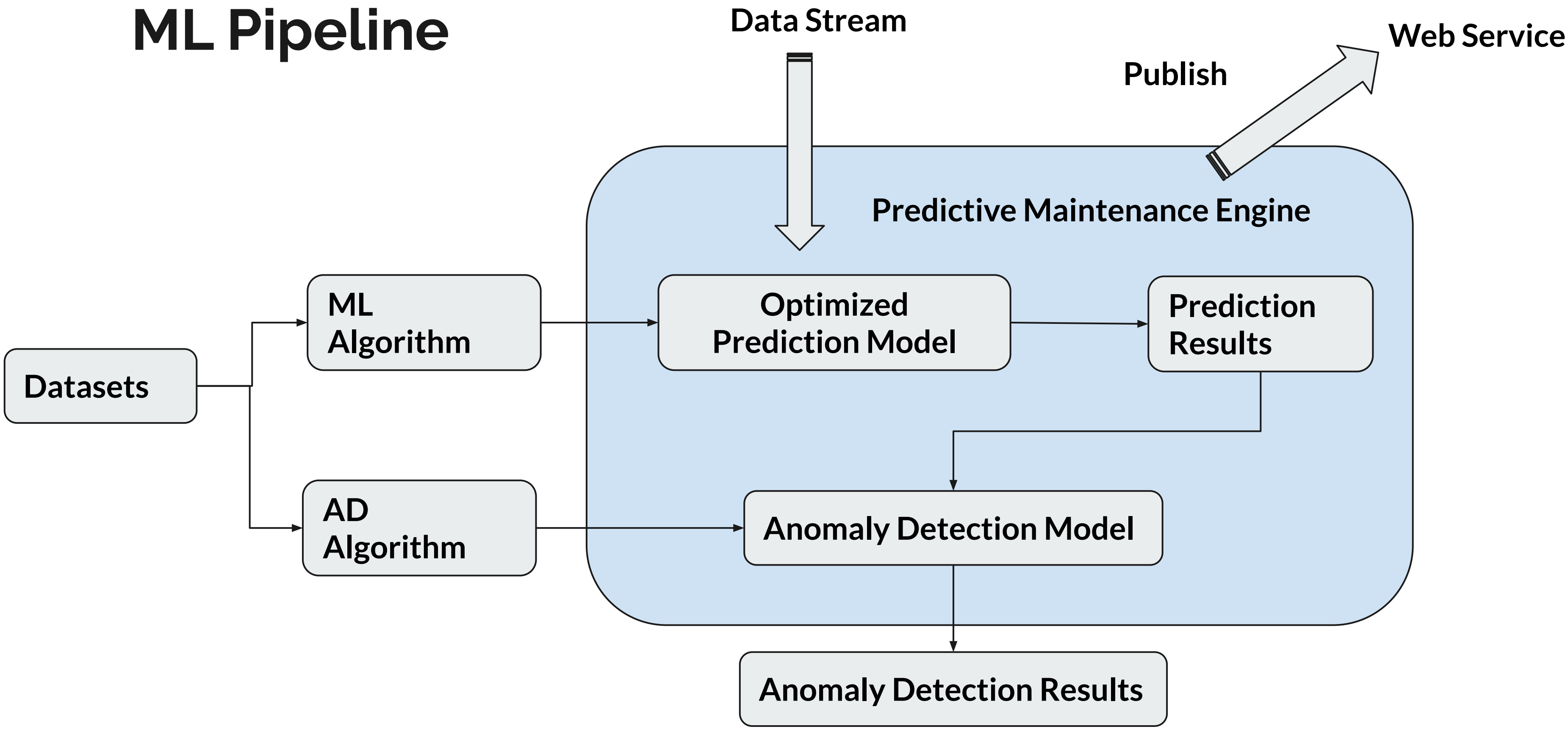


Improving anomaly detector

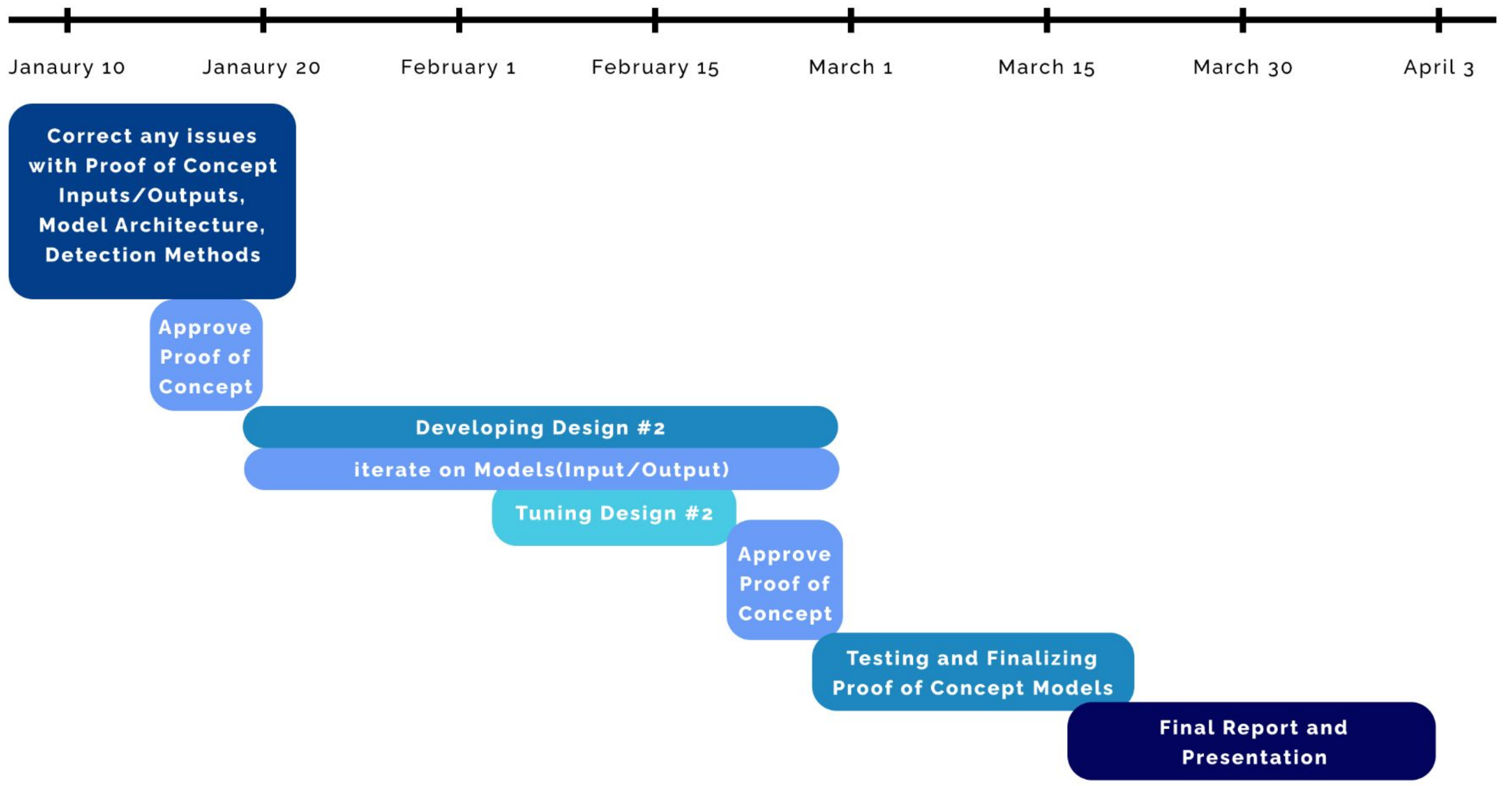
Once we include more insight and domain knowledge about when & how anomalies occur, we should ask:

- Are there more suitable algorithms?
- Are there points we should exclude?
- What, realistically, should the contamination fraction be?
- Should we fit all the data (costly) or just the last N entries?

ML Pipeline


Data Stream
Web Service
Publish
Predictive Maintenance Engine
ML
Algorithm
Optimized
Prediction Model
Prediction
Results
Datasets
AD
Algorithm
Anomaly Detection Model
Anomaly Detection Results

Project RoadMap



Thanks!

Any questions or Comments?