Auto encoder LSTM based error and anomaly detection experiment results

Table of Contents (LSTM Report)

Purpose:

The Aim of the experiments is to determine the relation between the LSTM window & anomaly trends, and also to distinguish between anomaly in sensor data & sensor faults.

Methodology:

EV dataset is used in different LSTM window sizes & error patterns are injected into the dataset. Later, the LSTM algorithm is tested on the dataset to see its effectiveness in finding the anomaly as well as sensor faults.

Codebase:
https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Anomaly-Detection

Configuration Scenario:

The experiment is considered to have the following configuration.

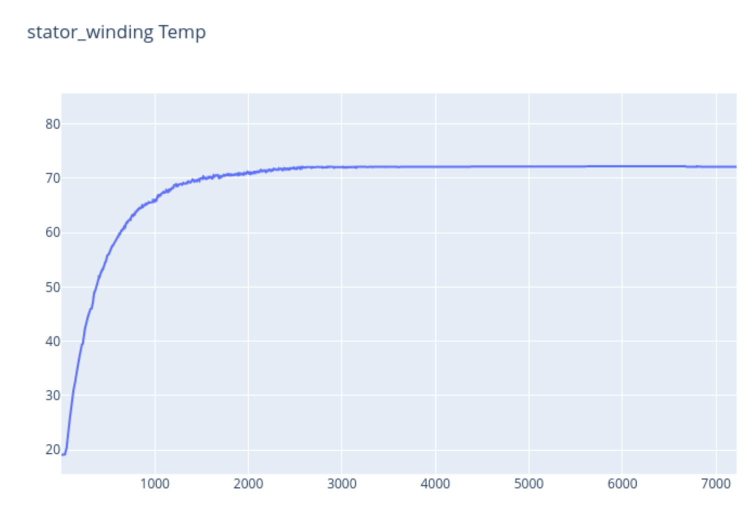
- A temperature sensor (range of 0*C to 100*C) is sensing the stator winding temperature of the motor and sending the data to northbound applications that host anomaly detection algorithms
- The base dataset is obtained from Kaggle and errors are injected in the “stator_winding” column as and when required

Part A (LSTM Timesteps<Error Window)

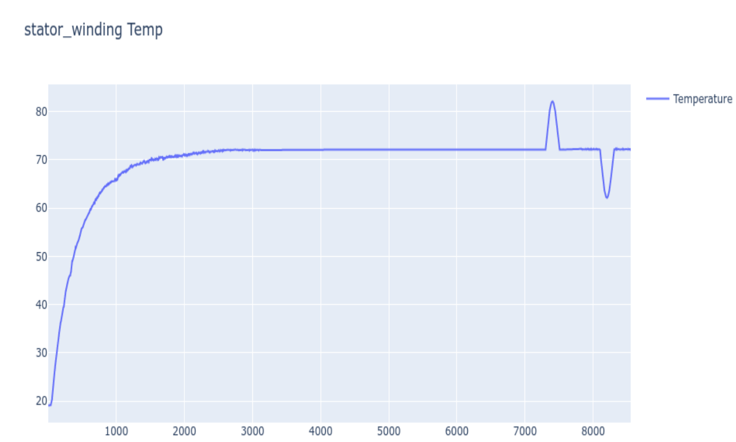
1. Data Vs Anomaly Plots Configuration:

- Dataset: EV stator winding Temp. vs Time (0.5 sec per datapoint)
- LSTM timesteps: 60 data points
- Epochs: 100
- Batch size: 60
- Error window: 200 data points
- Error injected as Sine, Square & Ramp wave
- Error injected as both Positive and Negative values in +Y axis

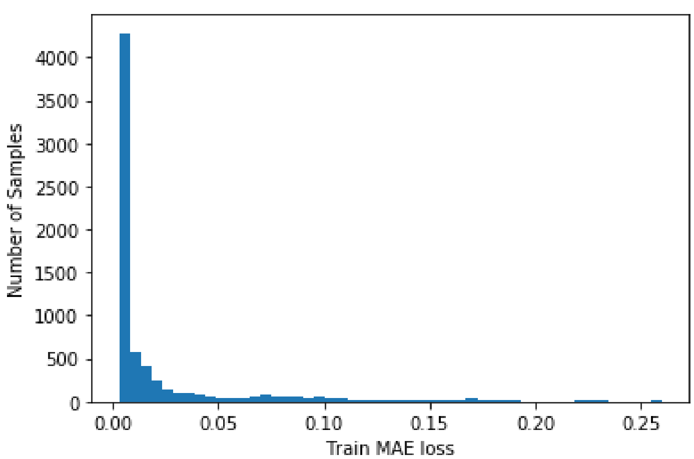
1.1 Sine Waveform error



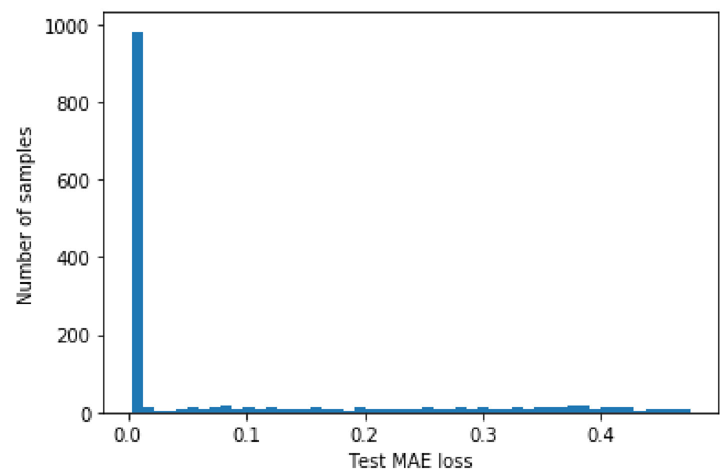
Training Dataset



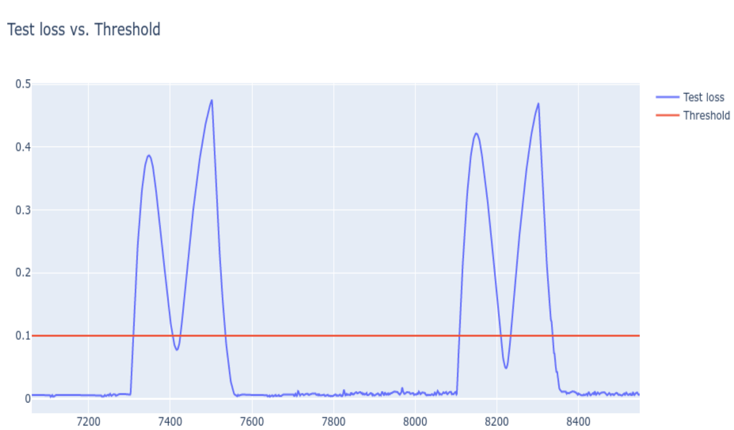
Sine Dataset



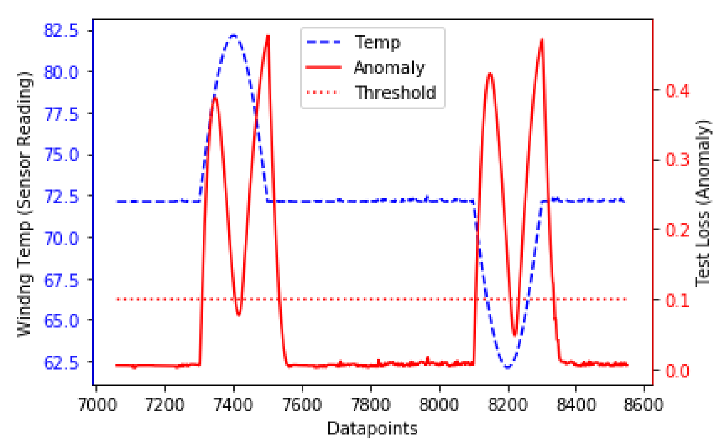
Sine Train MAE loss



Sine Test MAE loss



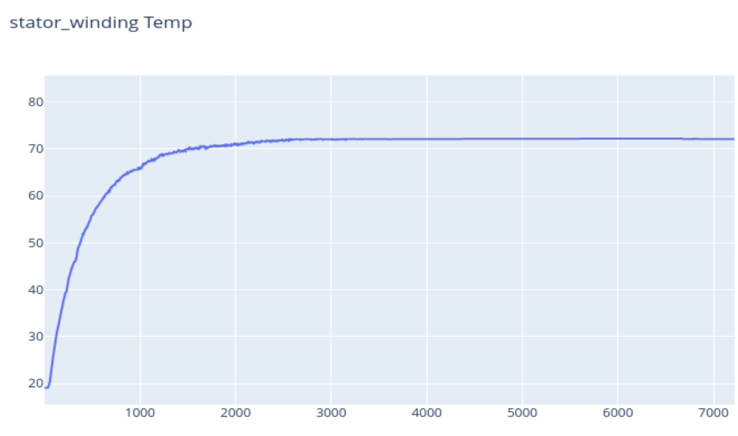
Sine Anomaly vs Threshold



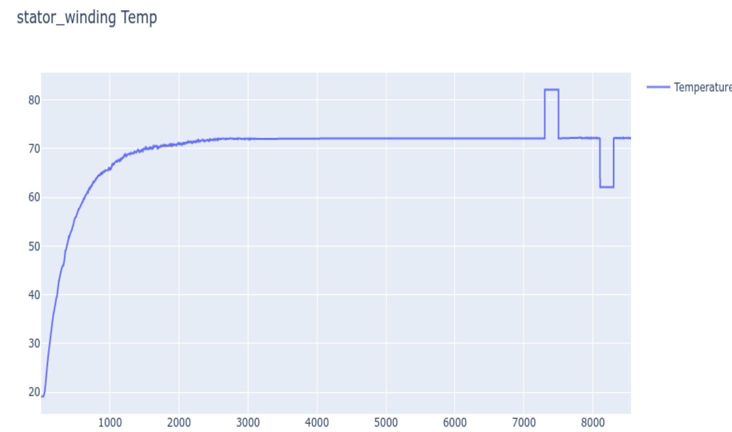
Sine Data vs Anomaly

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

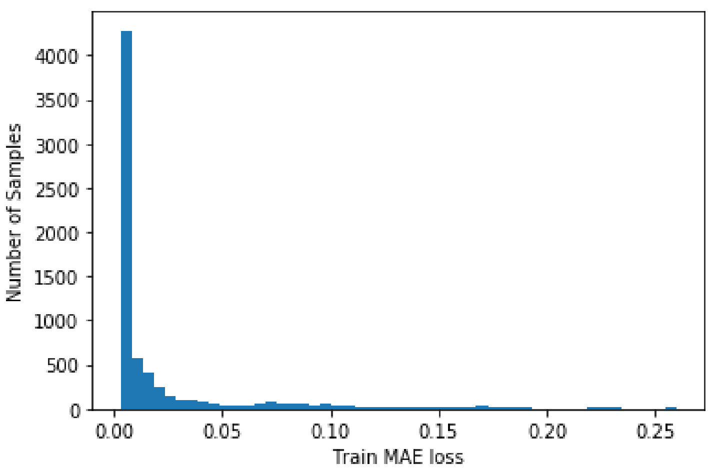
1.2 Square Waveform error



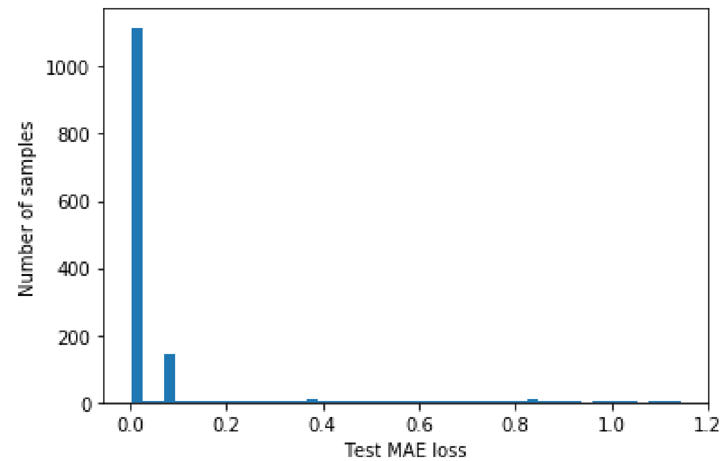
Training Dataset



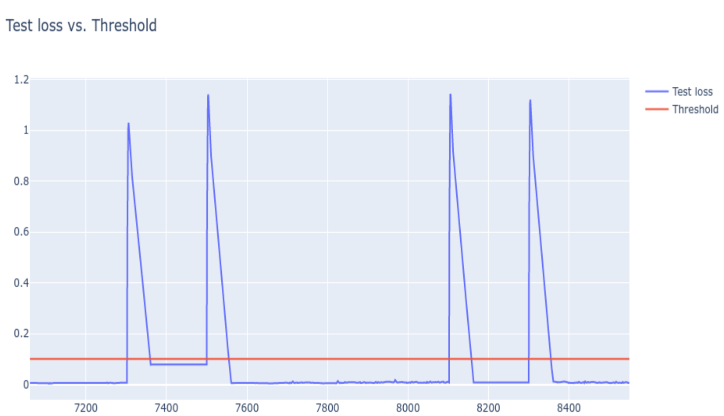
Square Dataset



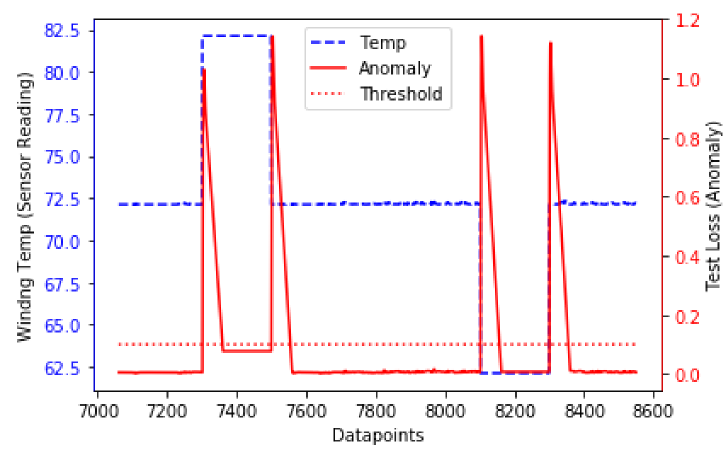
Square Train MAE loss



Square Test MAE loss



Square Anomaly vs Threshold



Square Data vs Anomaly

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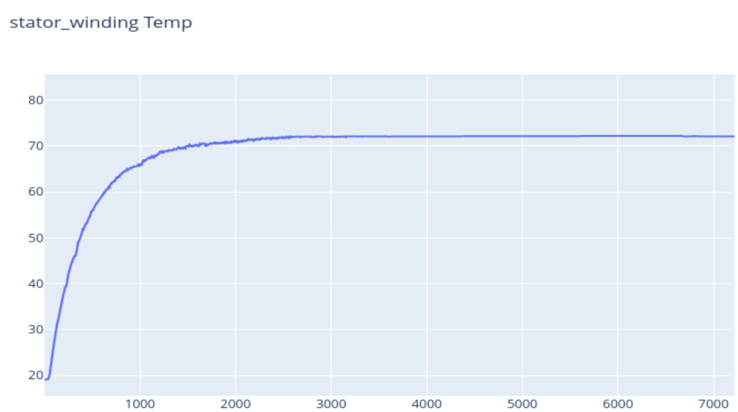
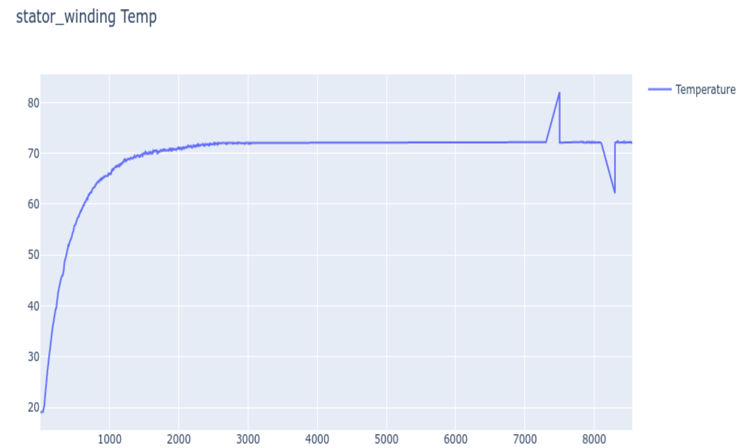
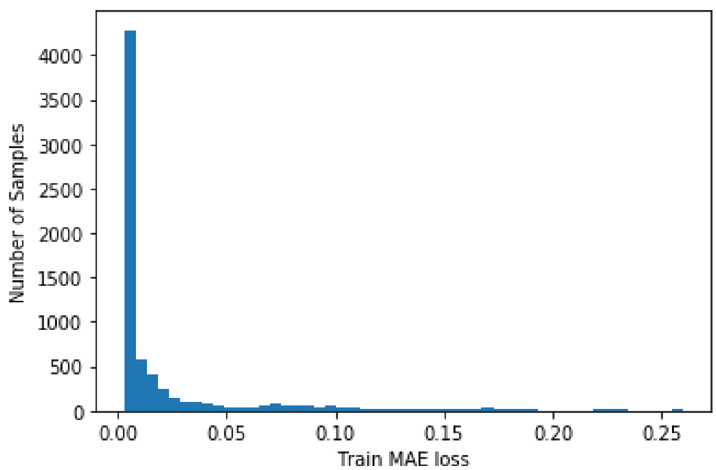
1.3 Ramp Waveform error



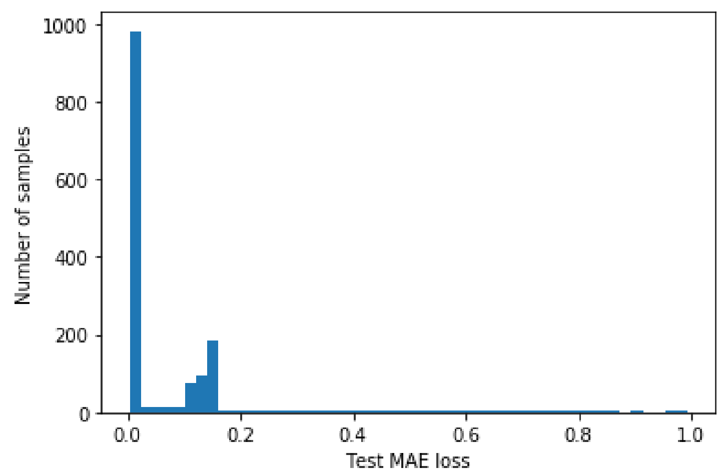
Training Dataset



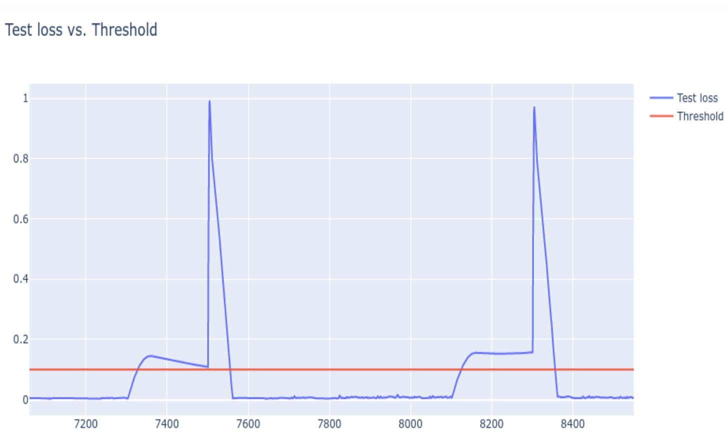
Ramp Dataset



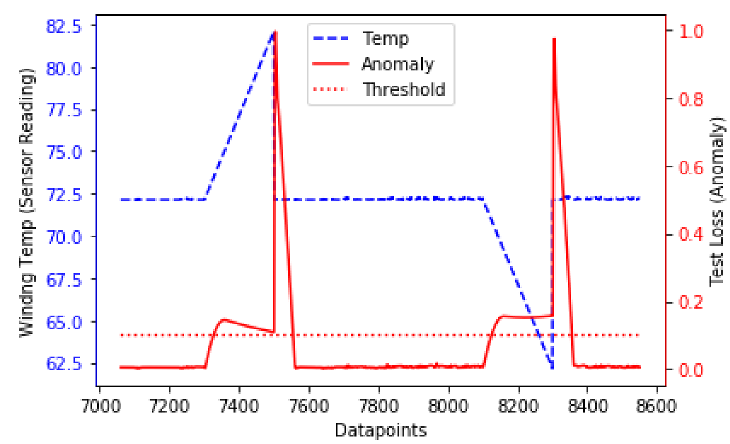
Ramp Train MAE loss



Ramp Test MAE loss



Ramp Anomaly vs Threshold



Ramp Data vs Anomaly

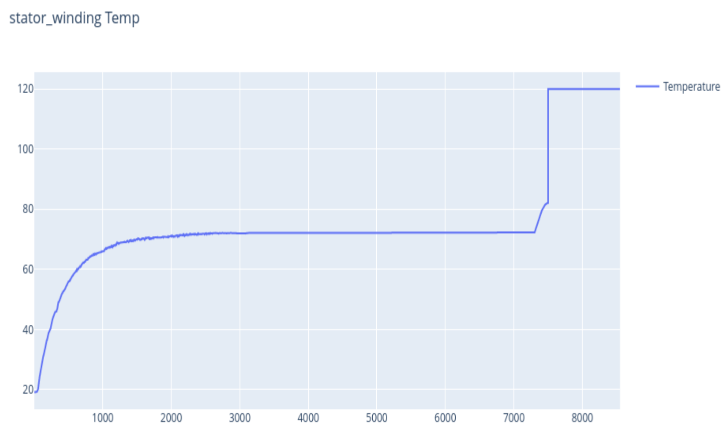
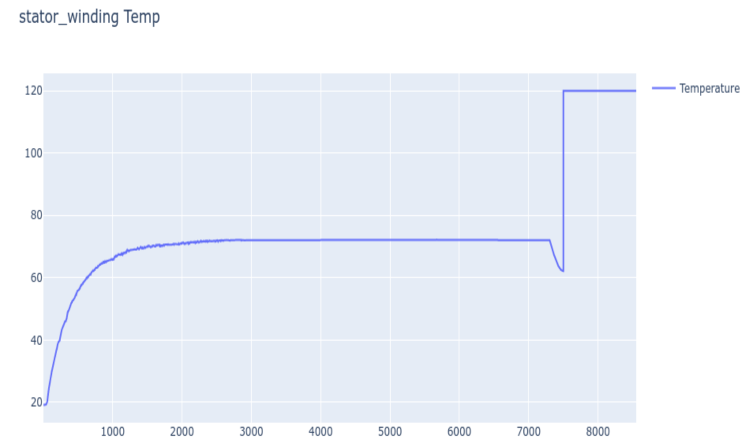
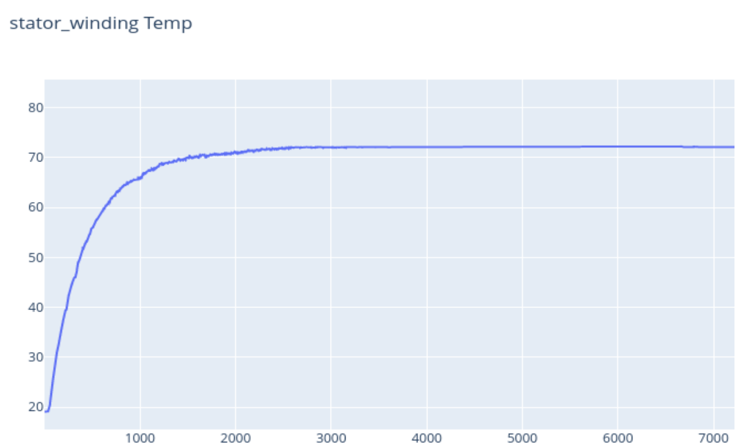
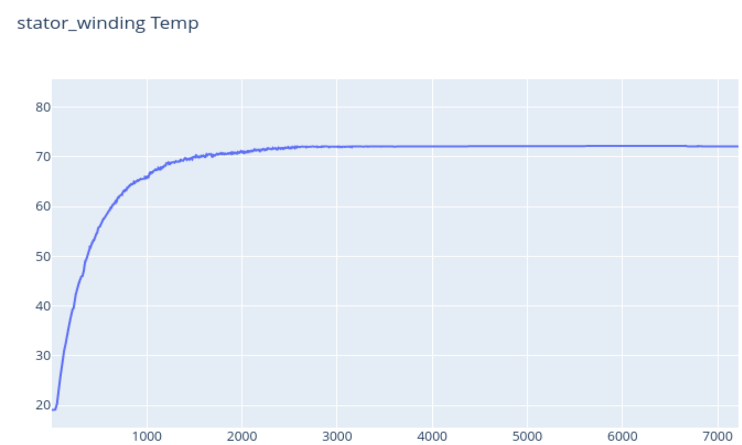
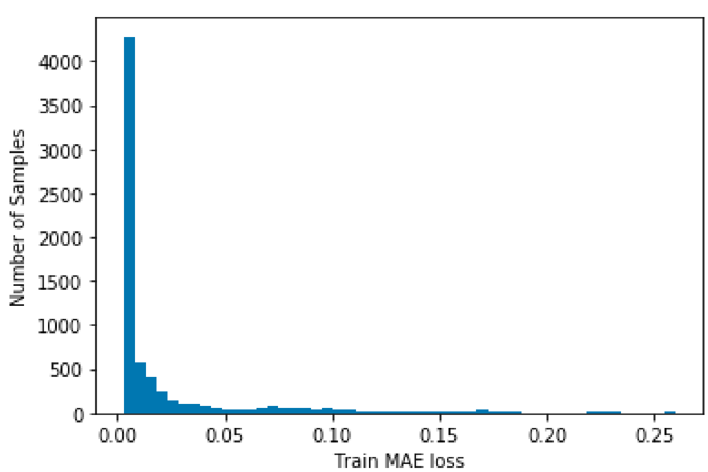
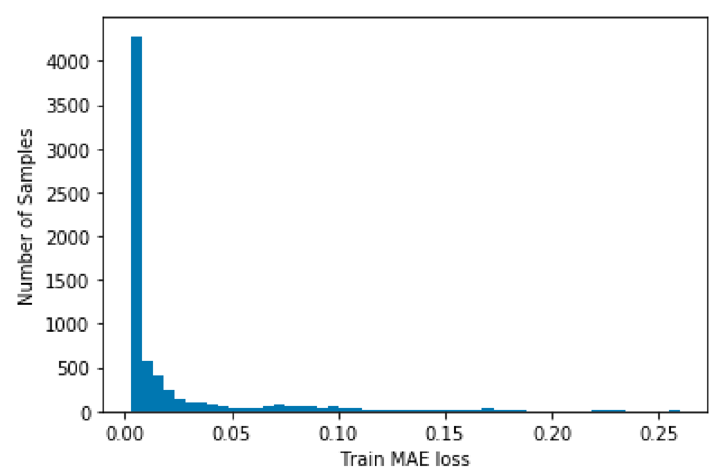
Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

2. Data Vs Fault Plots

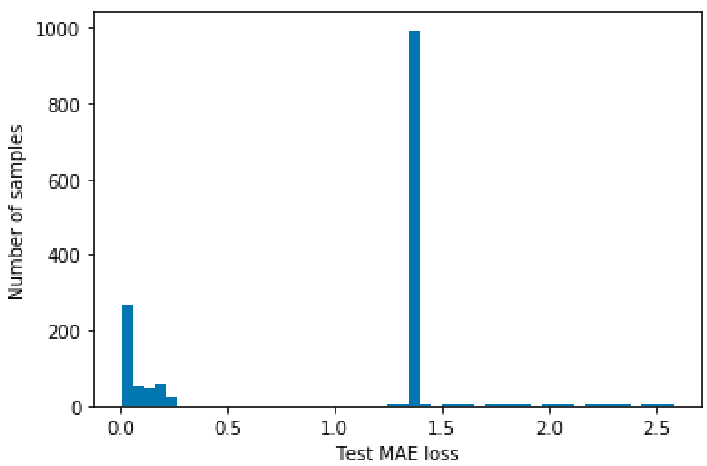
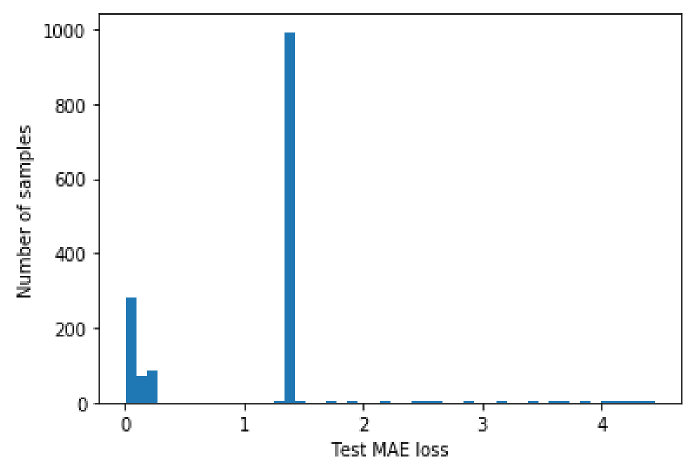
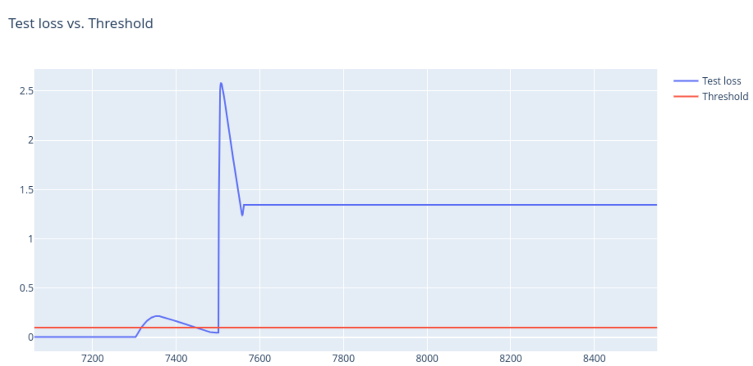
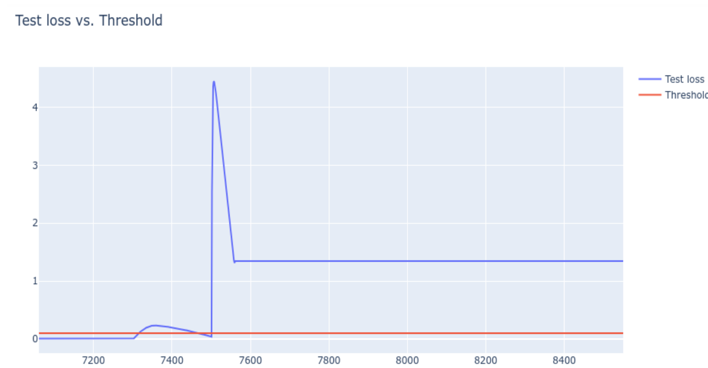
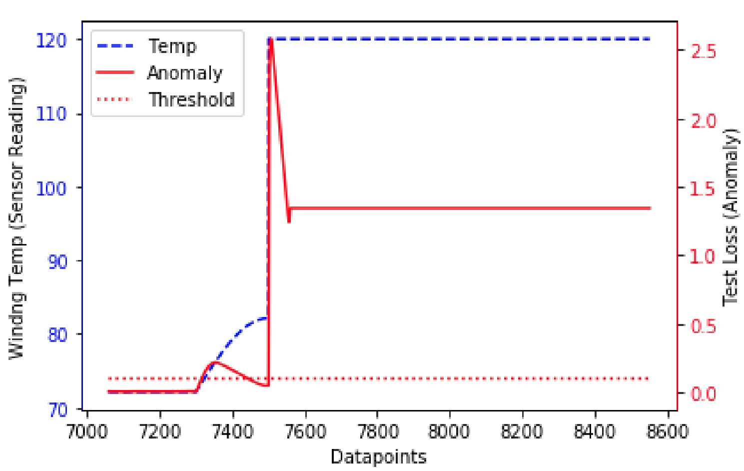
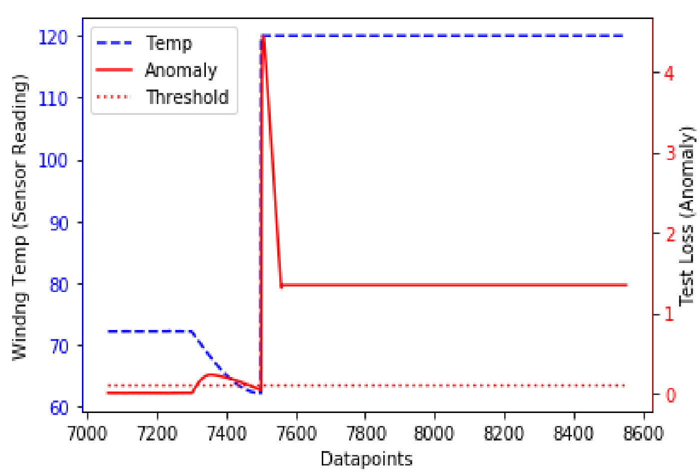
Configuration:

- Dataset: EV stator winding Temp. vs Time (0.5 sec per datapoint)
- LSTM window: 60 data points
- Error window: 200 data points
- Error injected as Sine, Square & Ramp wave
- Error injected as Positive and Negative values in +Y axis separately
- Operating range of the sensor is assumed from 0*C to 100*C,
- When the sensor is faulty, it will send the temp. that is beyond the operating range, i.e. -20*C and 120*C

2.1.1 Sine, Fault HIGH

Sine Error curve: Rising	Sine Error curve: Falling
 Sine Dataset	 Sine Dataset
 Training Dataset	 Training Dataset
 Train MAE loss	 Train MAE loss

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

Sine Error curve: Rising	Sine Error curve: Falling
 Sine Test MAE loss	 Sine Test MAE loss
 Sine Anomaly vs Fault	 Sine Anomaly vs Fault
 Sine Rising Data vs Fault	 Sine Falling Data vs Fault

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

<table>
<tr><th colspan="2">2.1.2 Sine, Fault LOW</th></tr>
<tr><th>Sine Error curve: Rising</th><th>Sine Error curve: Falling</th></tr>
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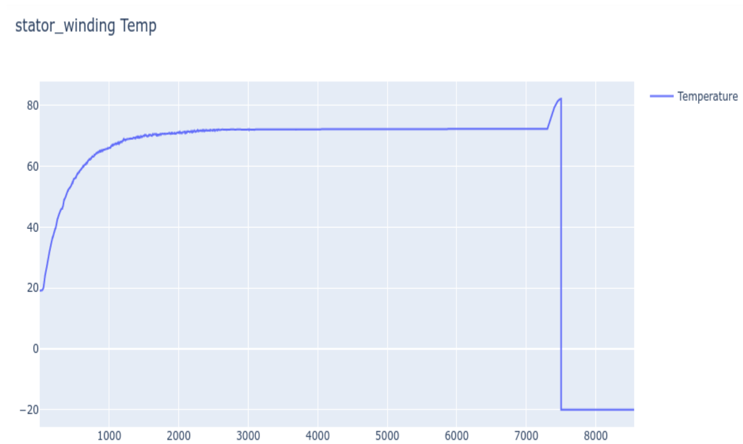

Sine Dataset
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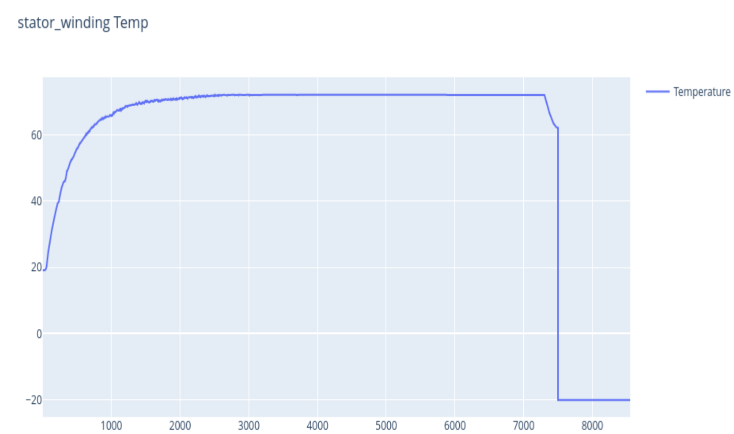

Sine Dataset
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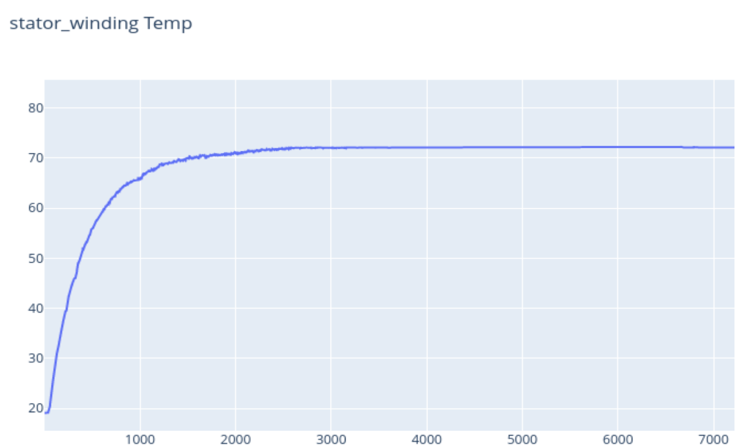

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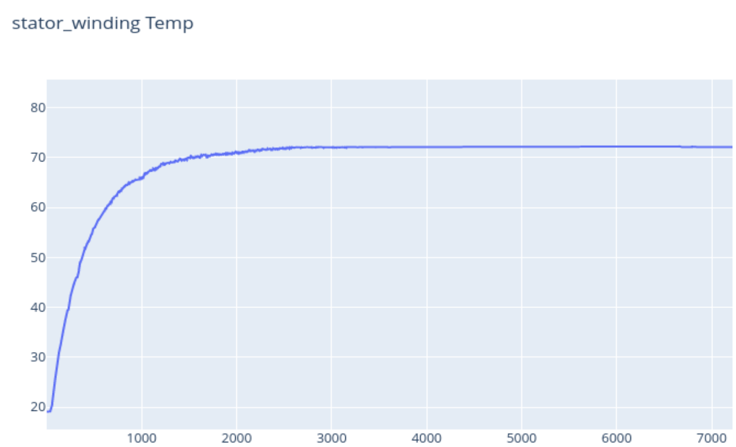

Training Dataset
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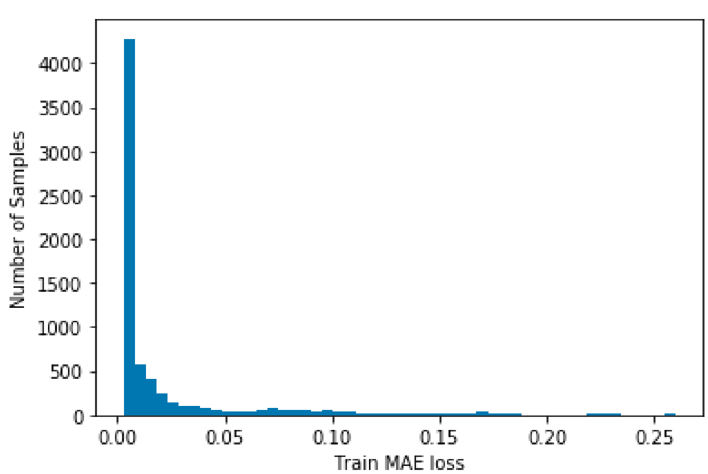

Train MAE loss
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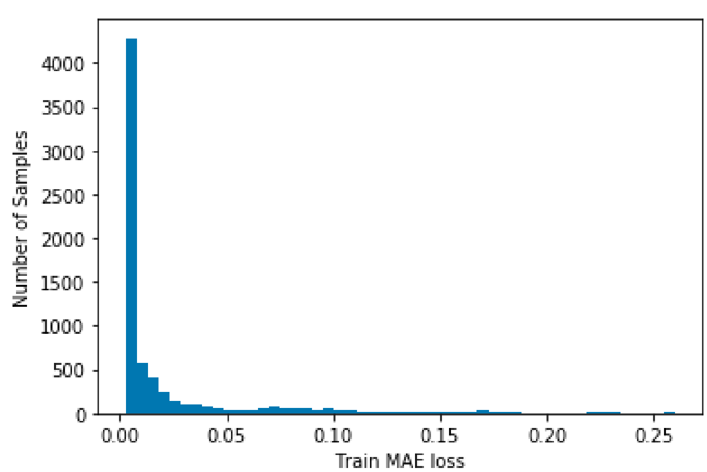

Train MAE loss
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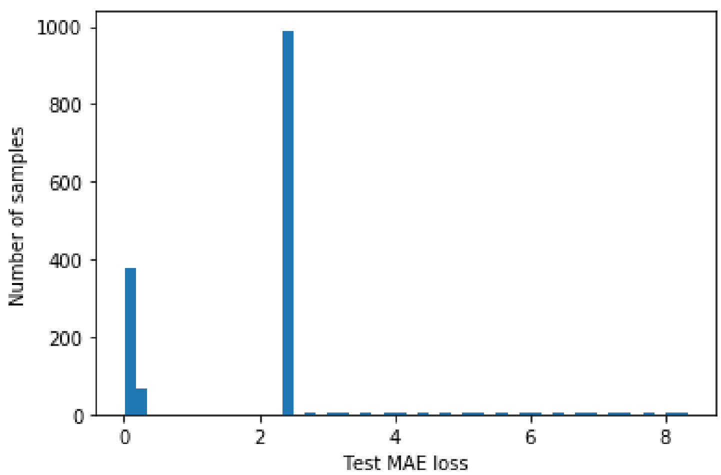
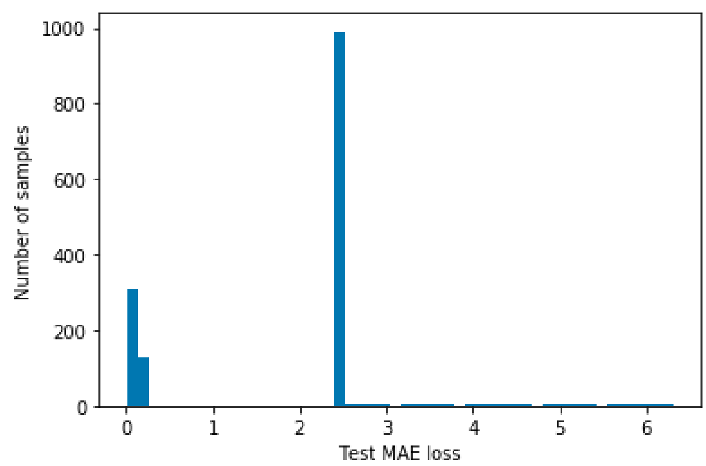
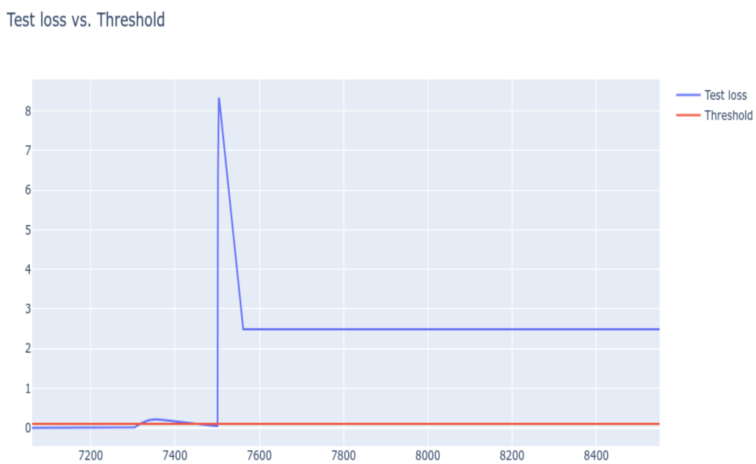
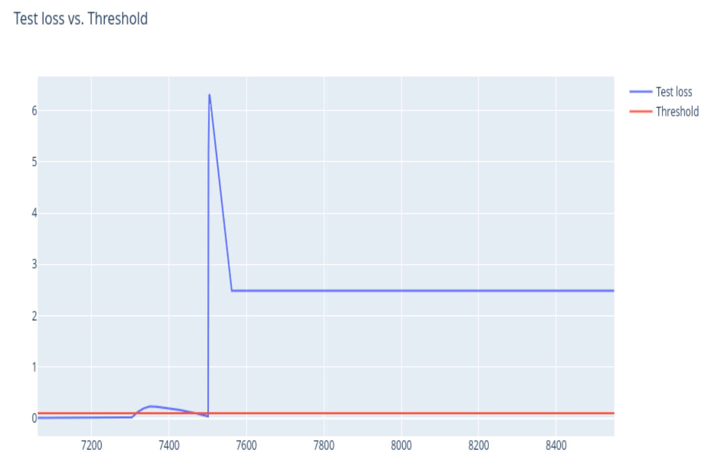
<tr><td>

Sine Test MAE loss</td><td>

Sine Test MAE loss</td></tr>
<tr><td>

Sine Anomaly vs Fault</td><td>

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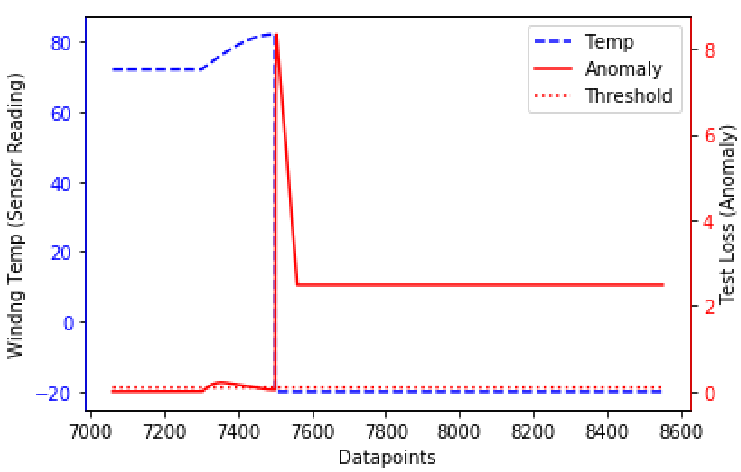
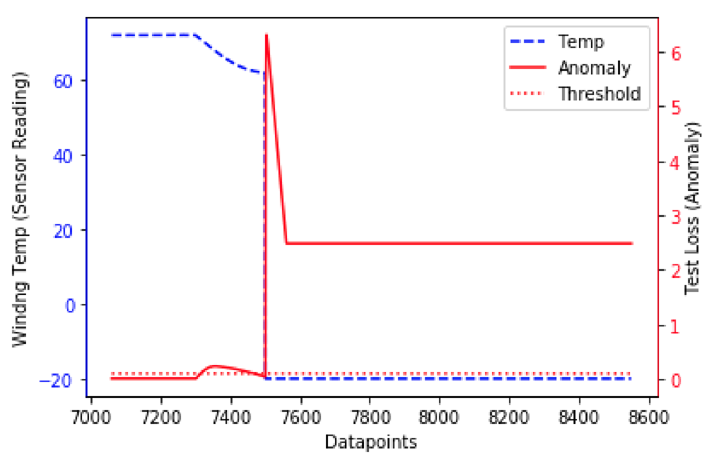
<tr><td>

Sine Rising Data vs Fault</td><td>

Sine Falling Data vs Fault</td></tr>
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2.2.1 Square, Fault HIGH

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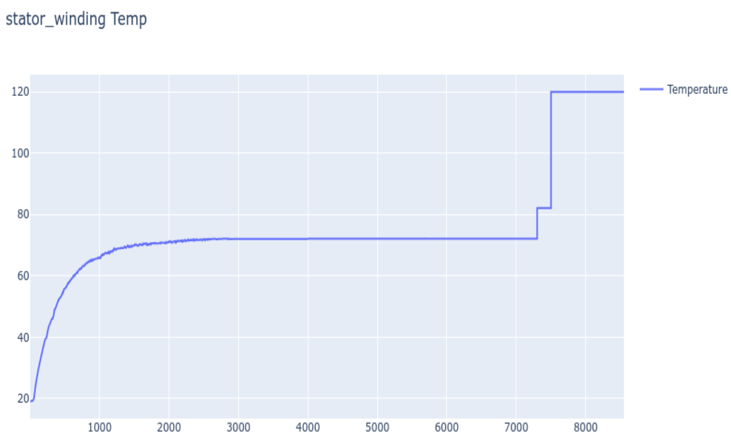
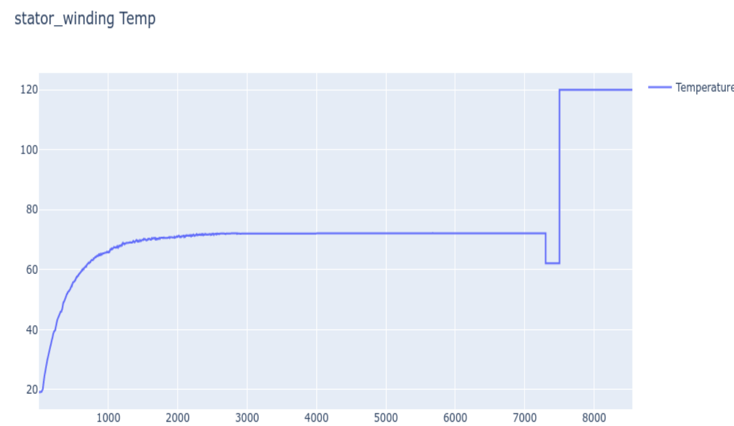
<tr><td>

Square Dataset</td><td>

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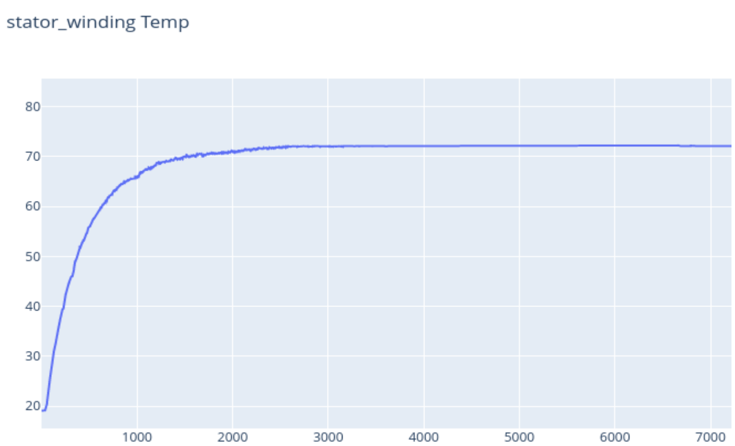
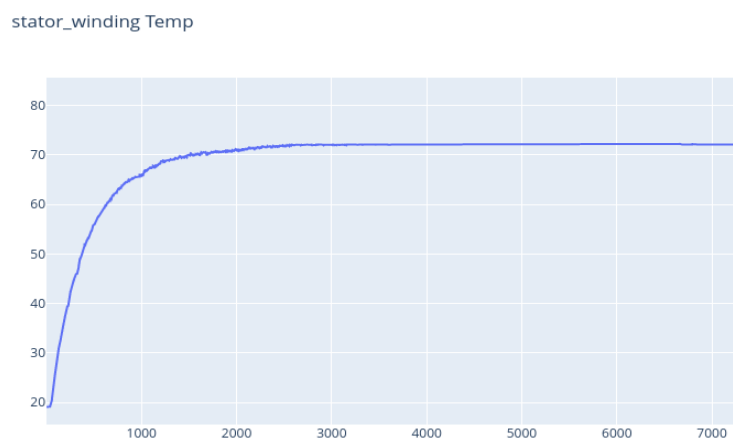
<tr><td>

Training Dataset</td><td>

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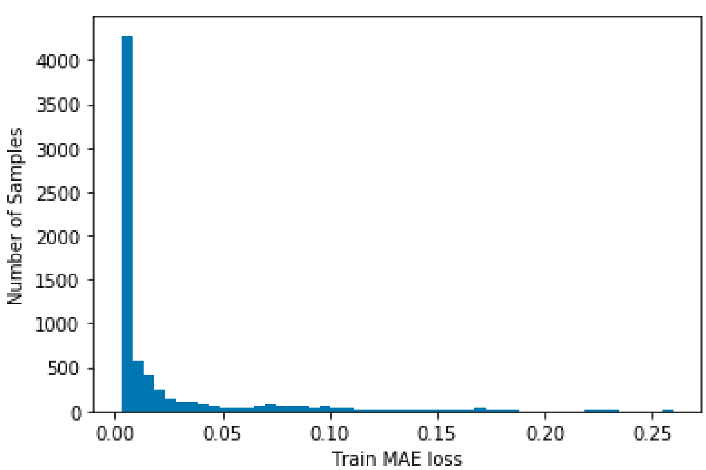
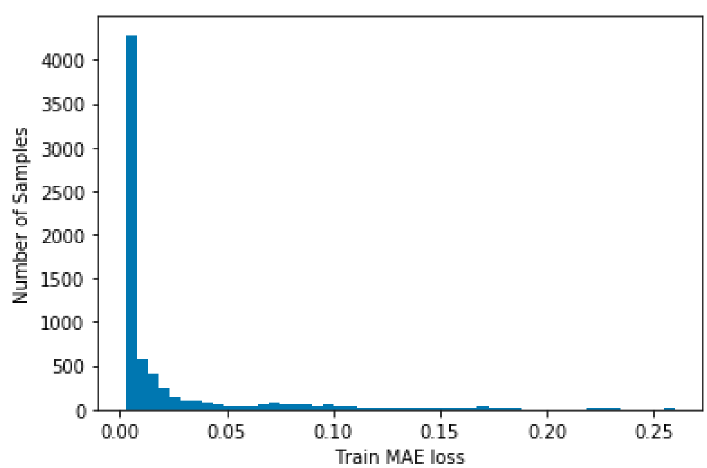
<tr><td>

Train MAE loss</td><td>

Train MAE loss</td></tr>
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Square Error curve: Rising	Square Error curve: Falling

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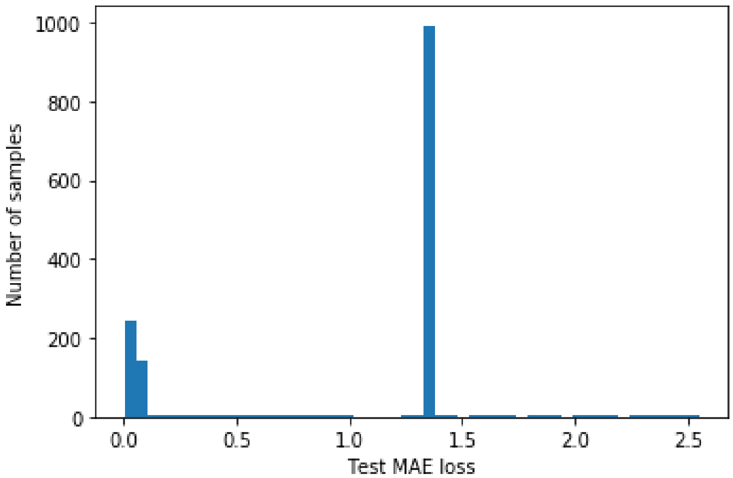
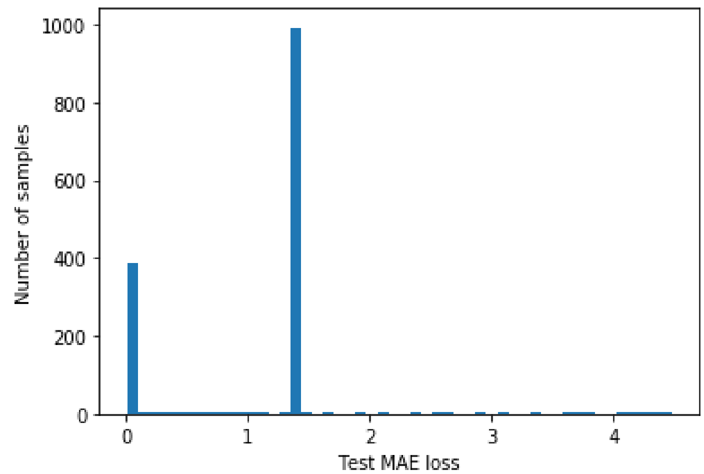


Square Test MAE loss



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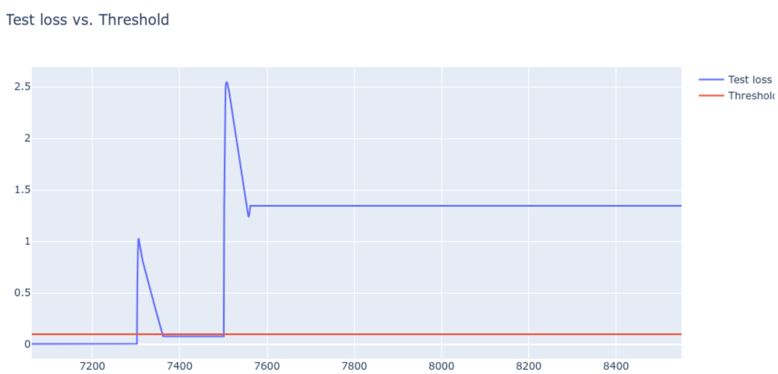
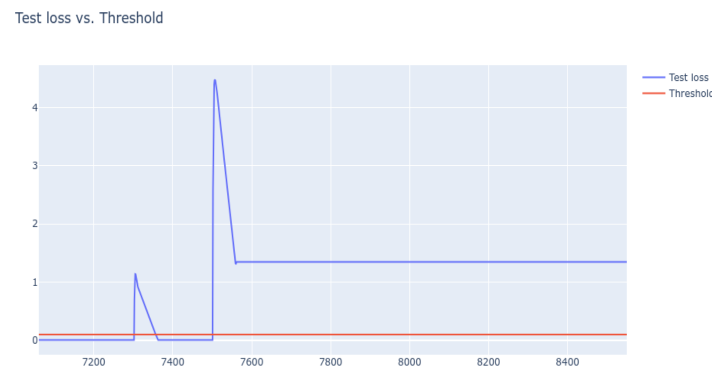
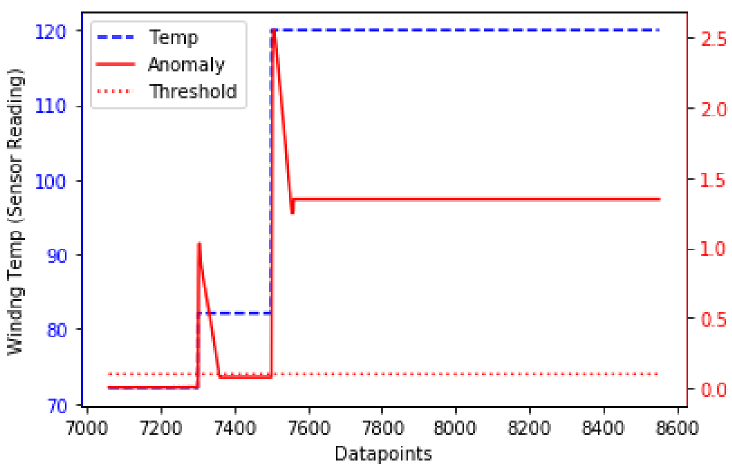


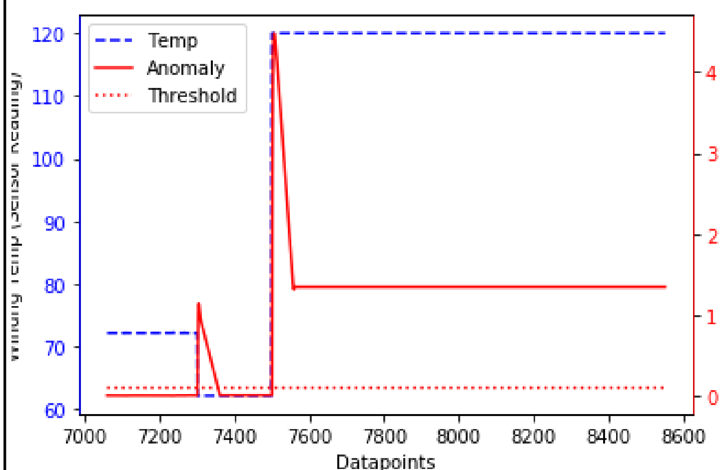
Square Anomaly vs Fault



Square Anomaly vs Fault



Square Rising Data vs Fault



Square Falling Data vs Fault

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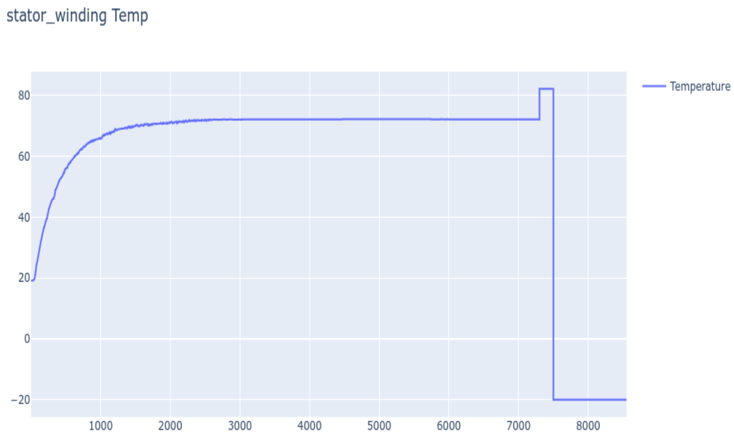
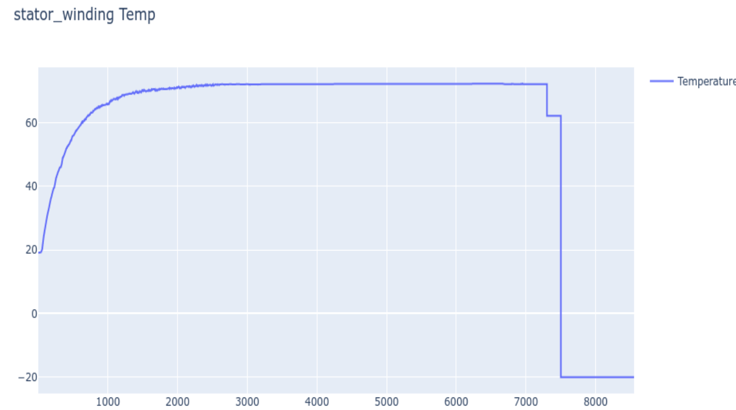
<tr><td>

Square Dataset</td><td>

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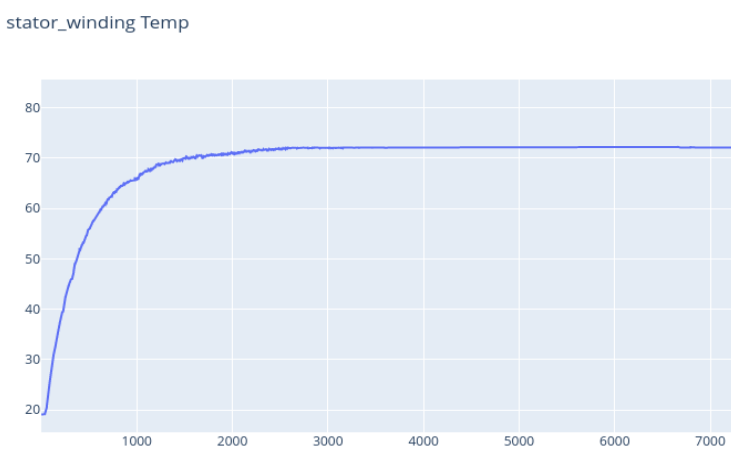
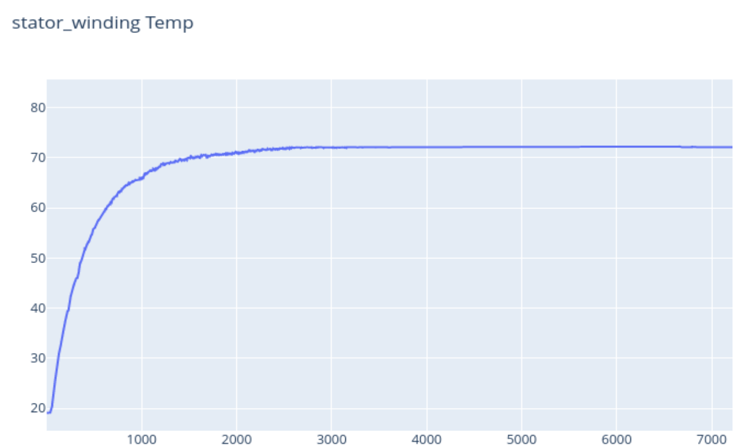
<tr><td>

Training Dataset</td><td>

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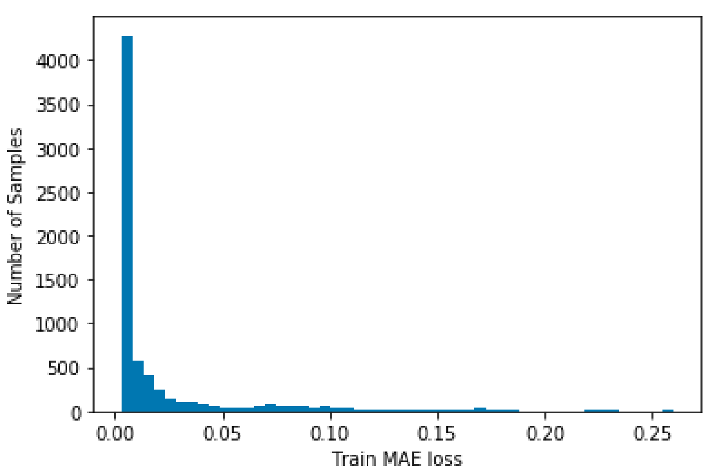
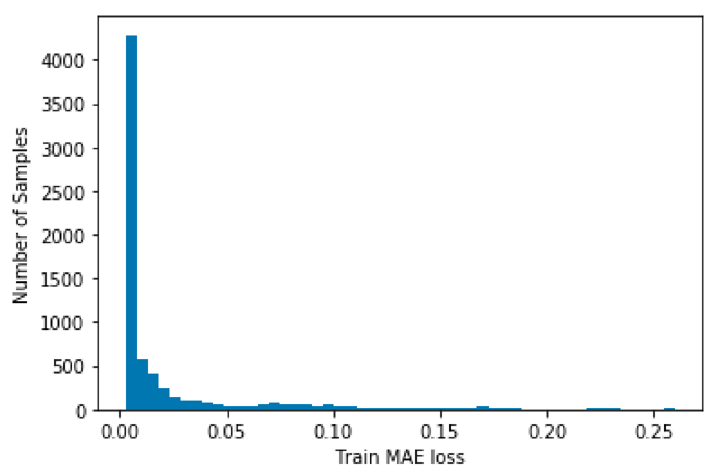
<tr><td>

Train MAE loss</td><td>

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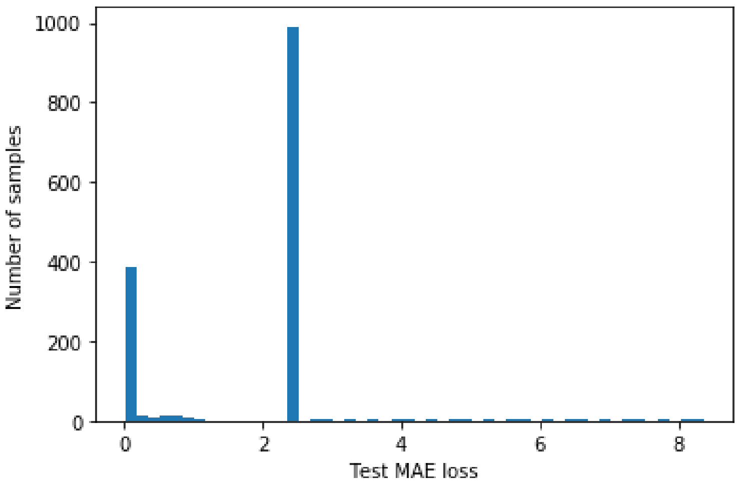

Square Test MAE loss

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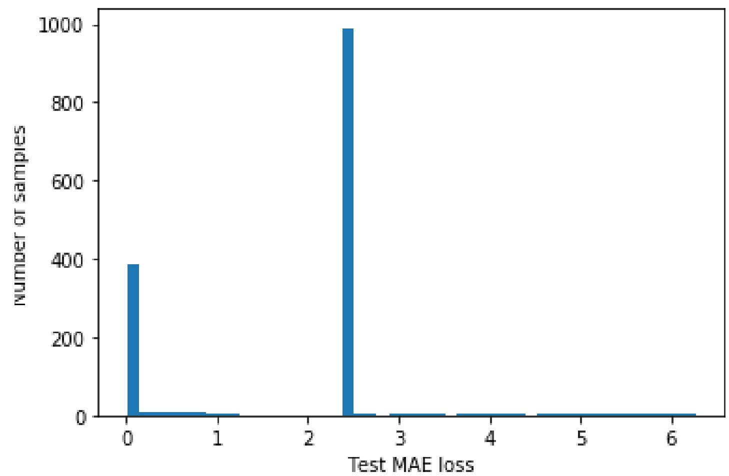

Square Test MAE loss

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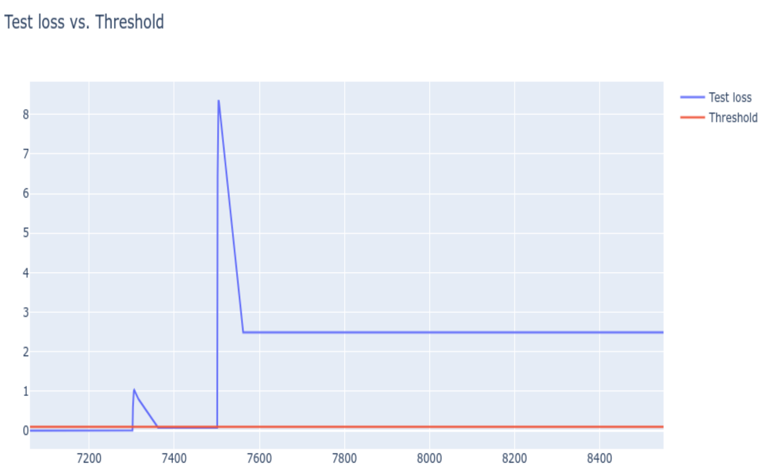
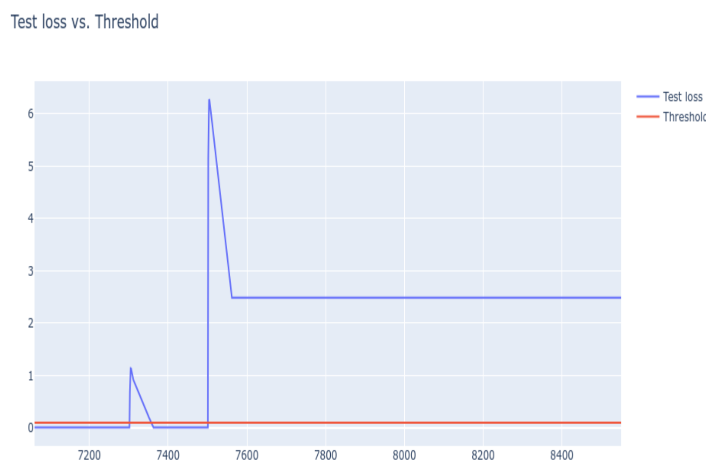


Square Anomaly vs Fault

</td><td>



Square Anomaly vs Fault

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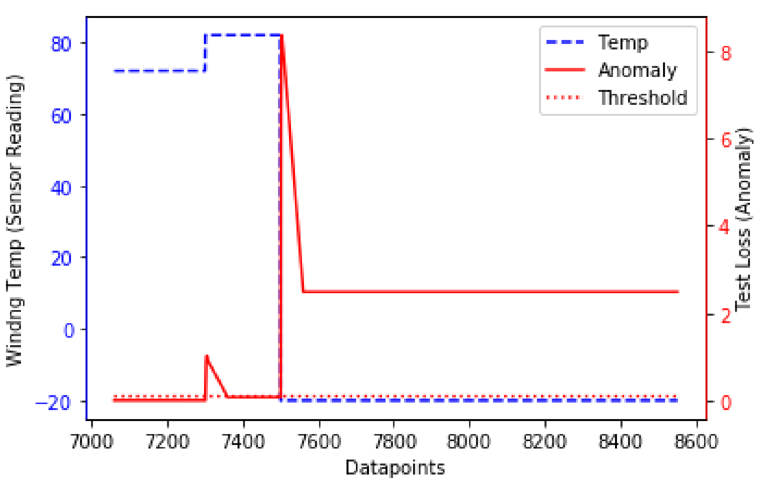

Square Rising Data vs Fault

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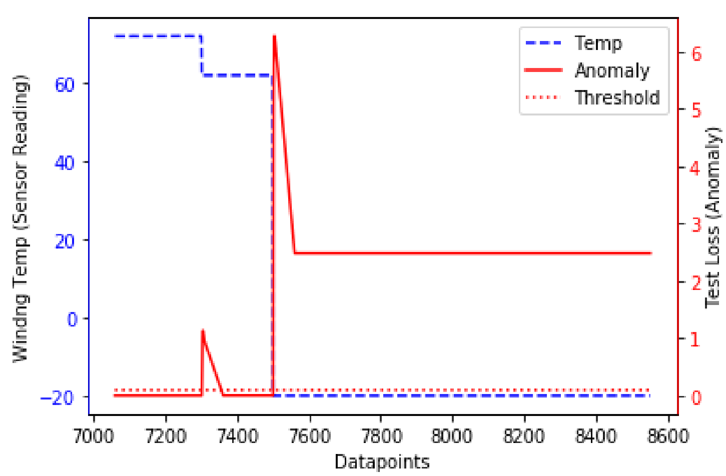

Square Falling Data vs Fault

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Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

<table>
<tr><th colspan="2">2.3.1 Ramp, Fault HIGH</th></tr>
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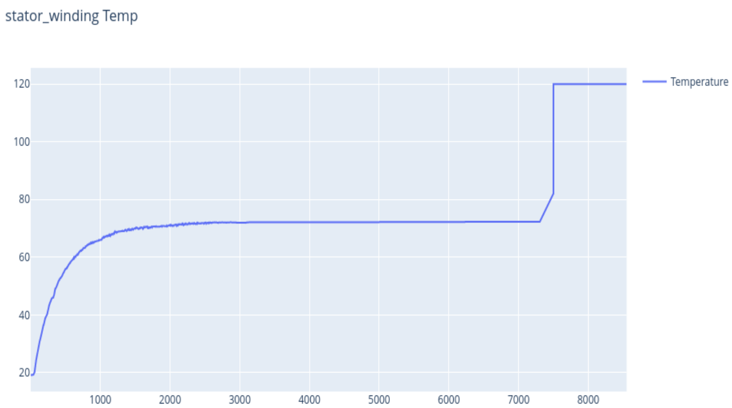
<td>

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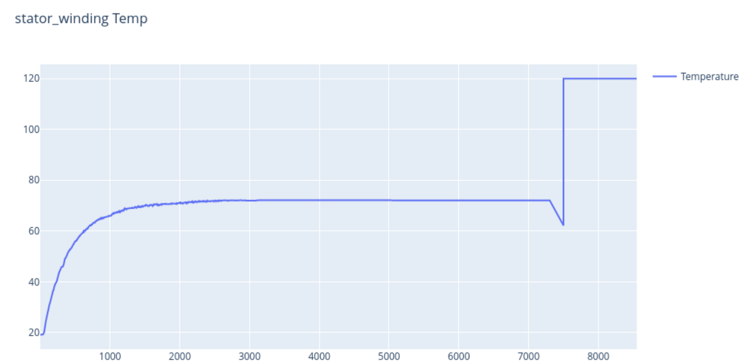
<td>

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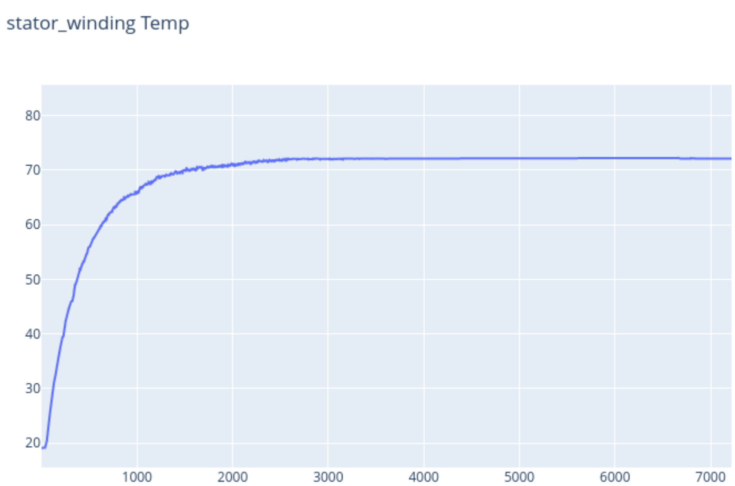
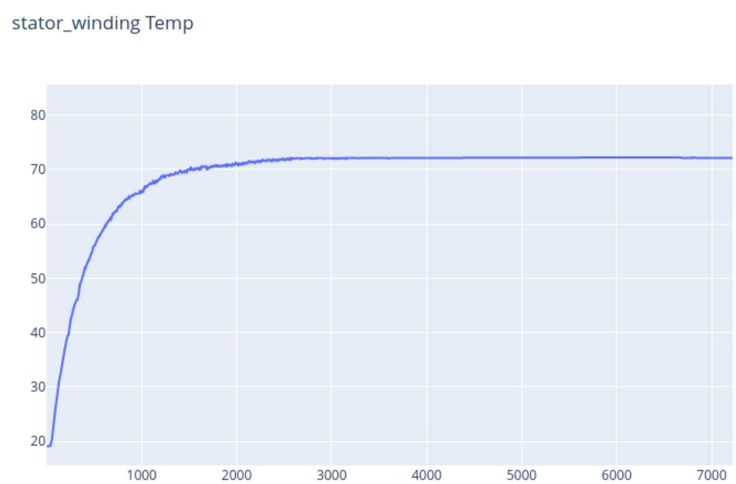
<td>

Training Dataset</td>
<td>

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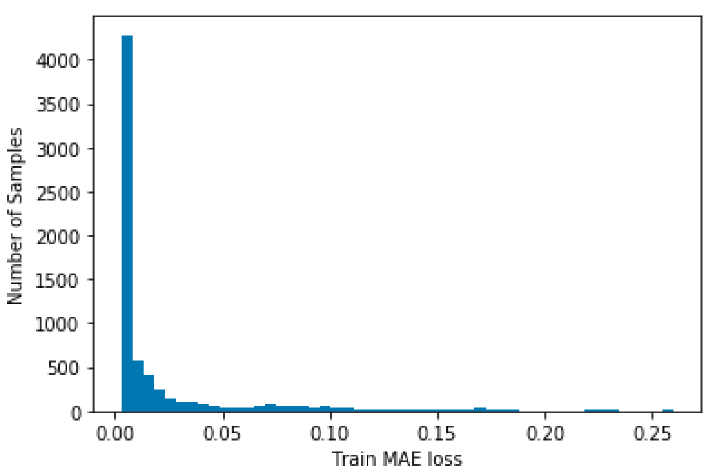
<td>

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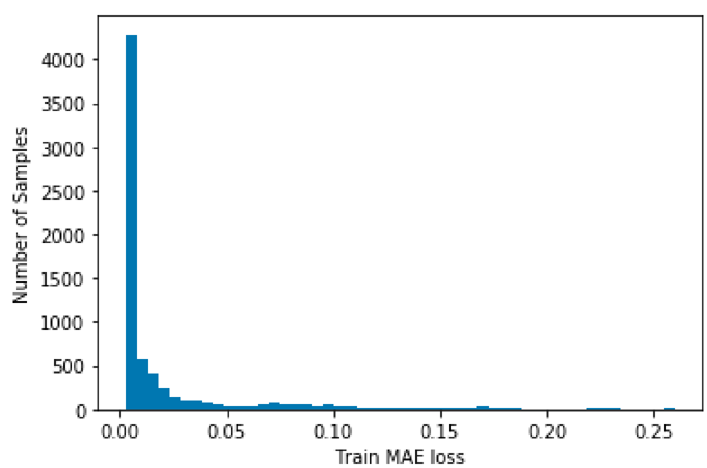
<td>

Train MAE loss</td>
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Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

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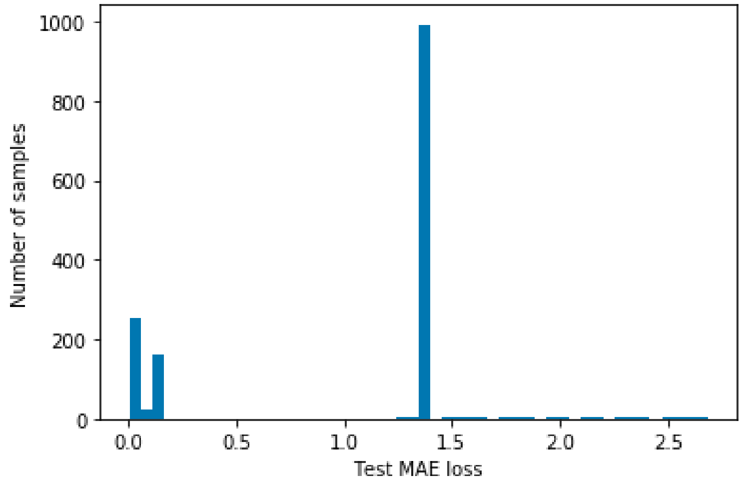

Ramp Test MAE loss
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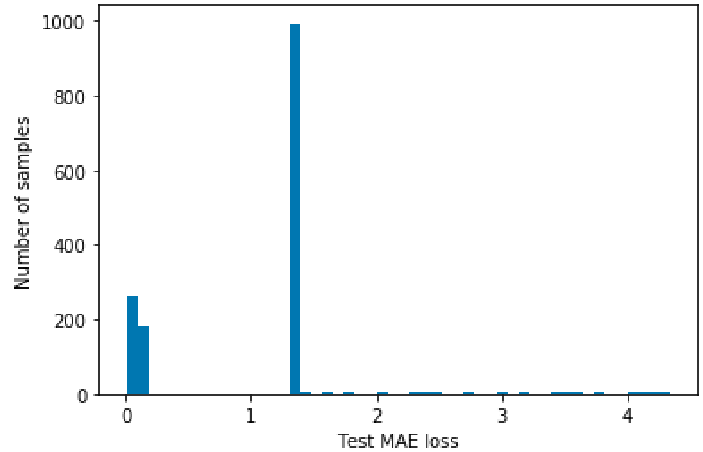

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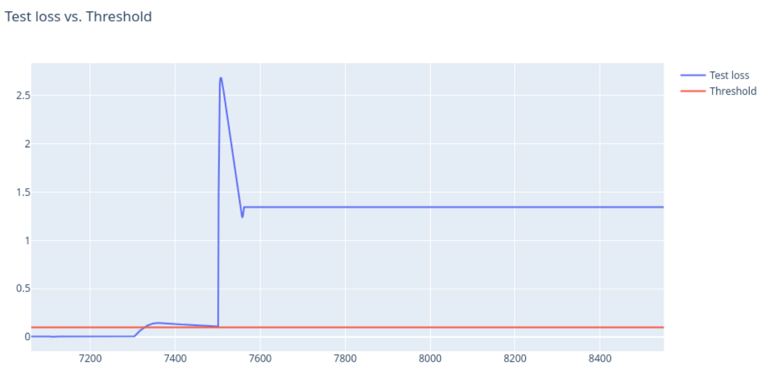

Ramp Anomaly vs Fault
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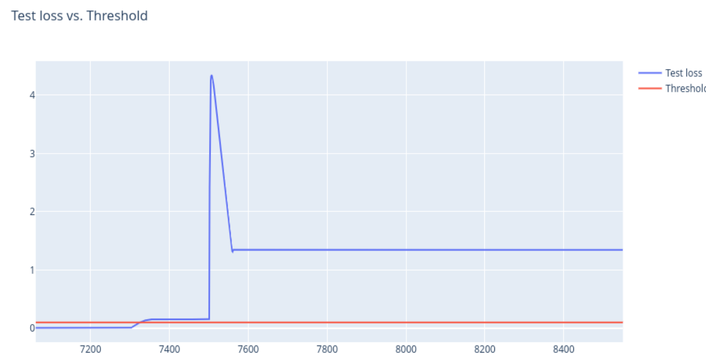

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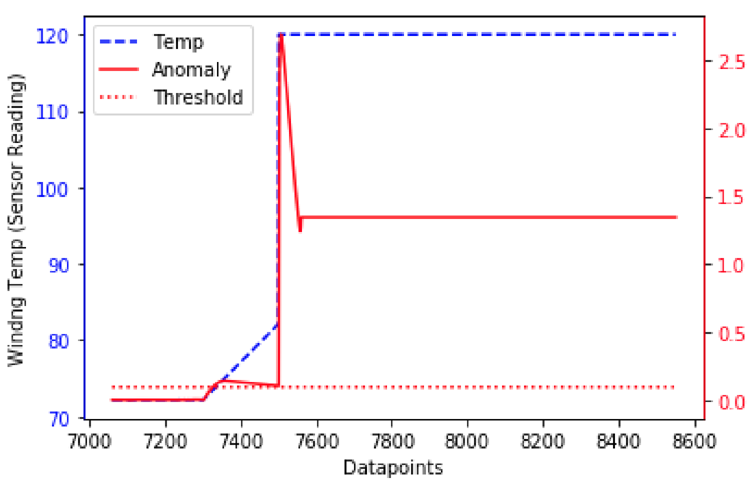

Ramp Rising Data vs Fault
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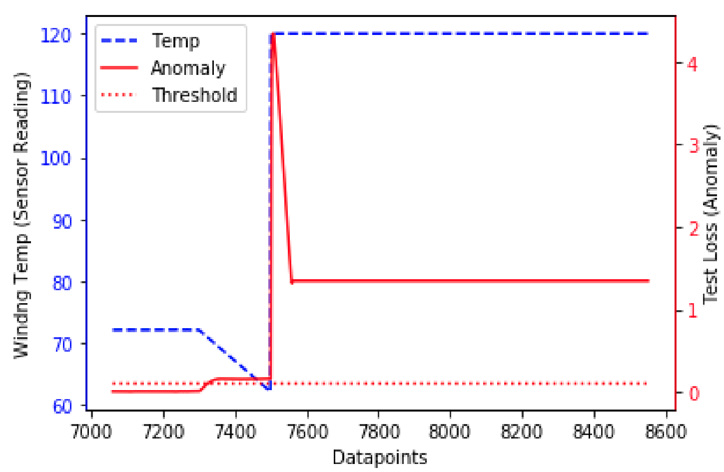

Ramp Falling Data vs Fault
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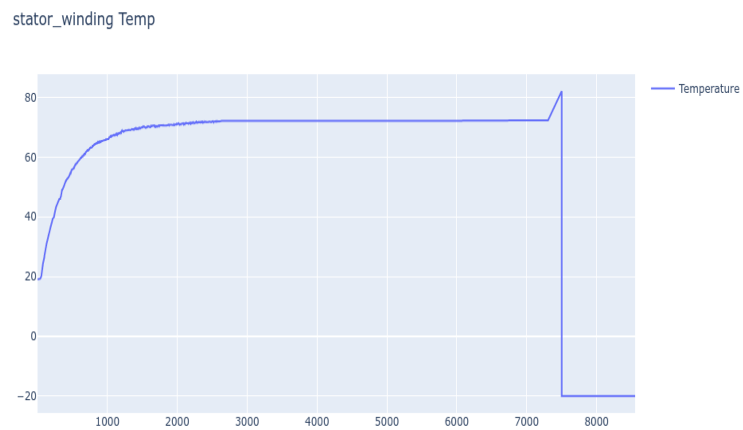
Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

2.3.2 Ramp, Fault LOW

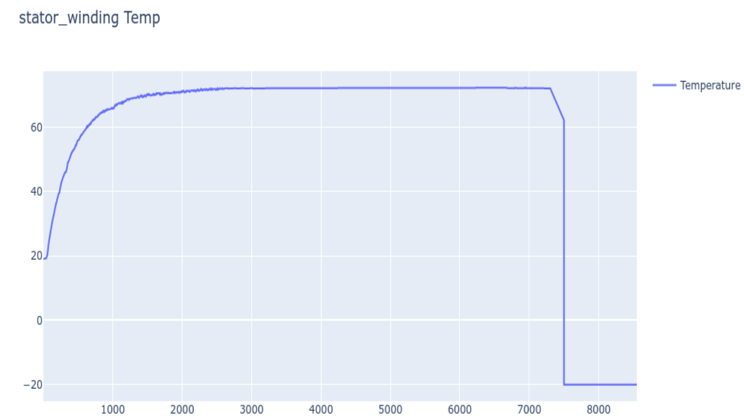
Ramp Error curve: Rising	Ramp Error curve: Falling

Ramp Error curve: Rising

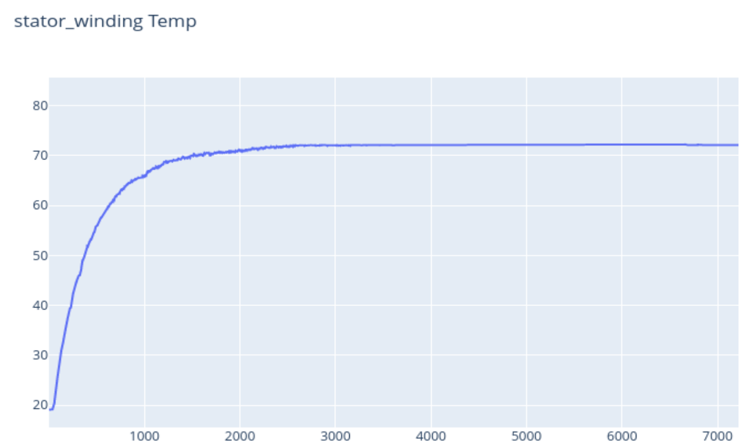


Ramp Dataset

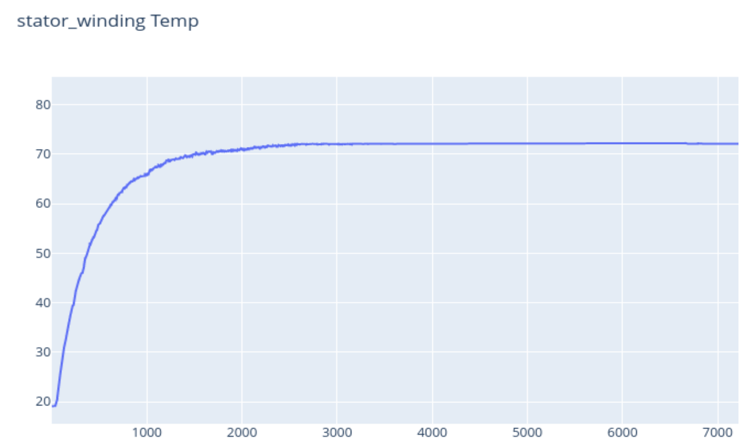
Ramp Error curve: Falling



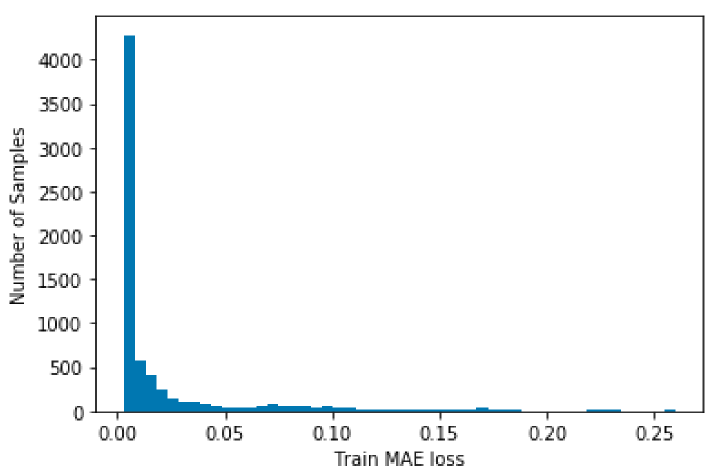
Ramp Dataset



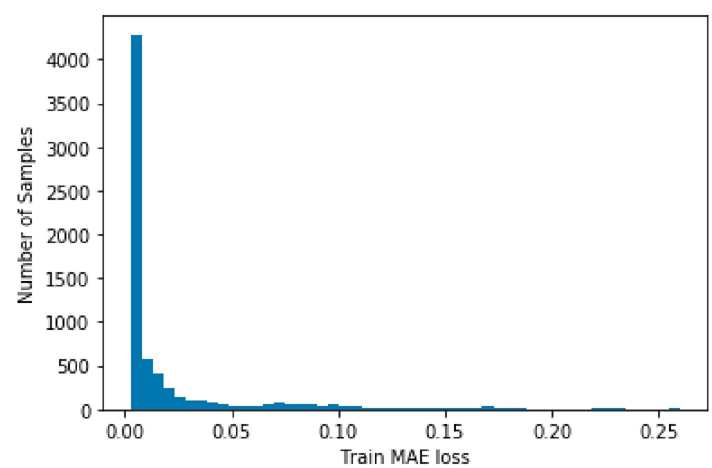
Training Dataset



Training Dataset



Train MAE loss



Train MAE loss

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

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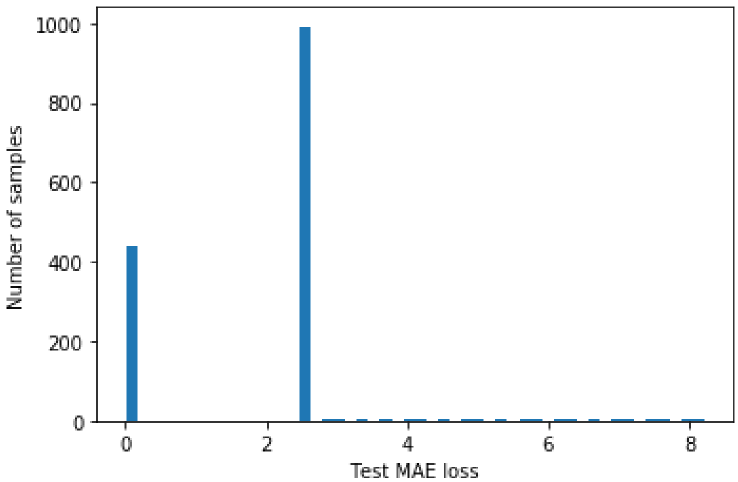

Ramp Test MAE loss
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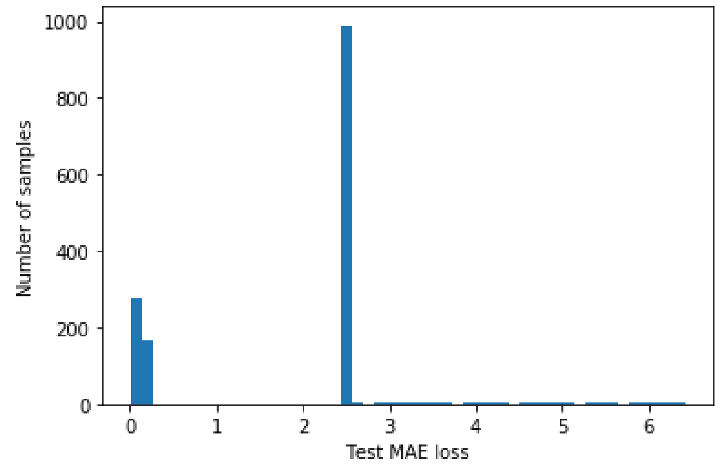

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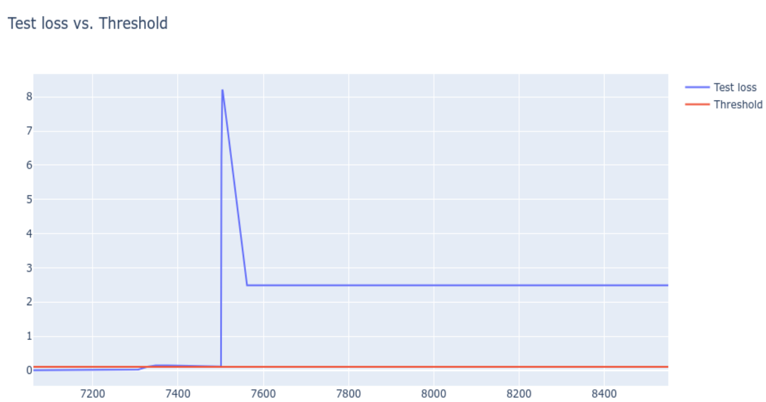

Ramp Anomaly vs Fault
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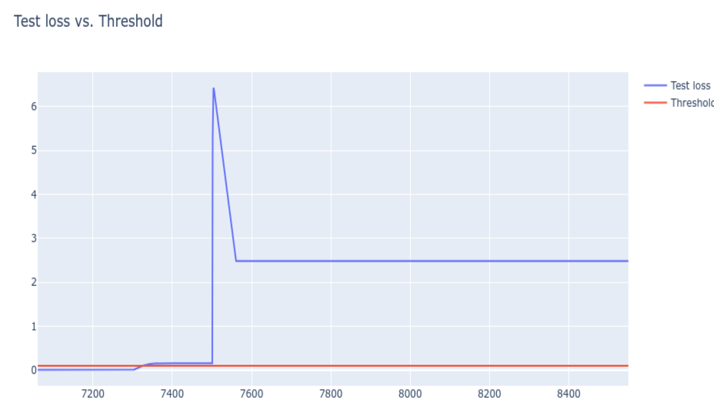

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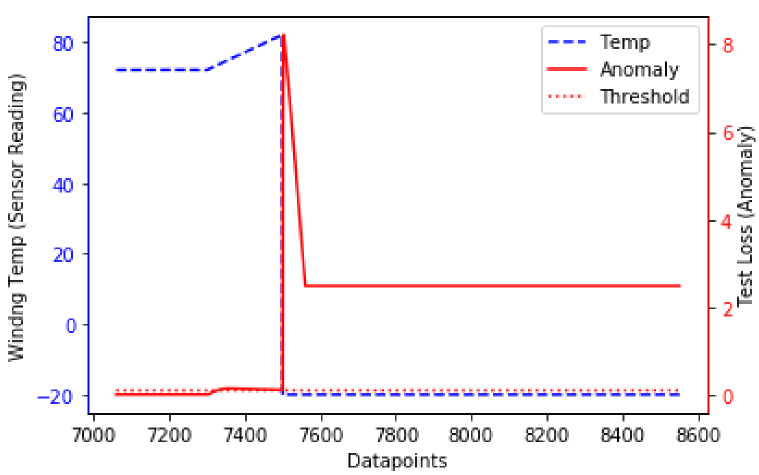

Ramp Rising Data vs Fault
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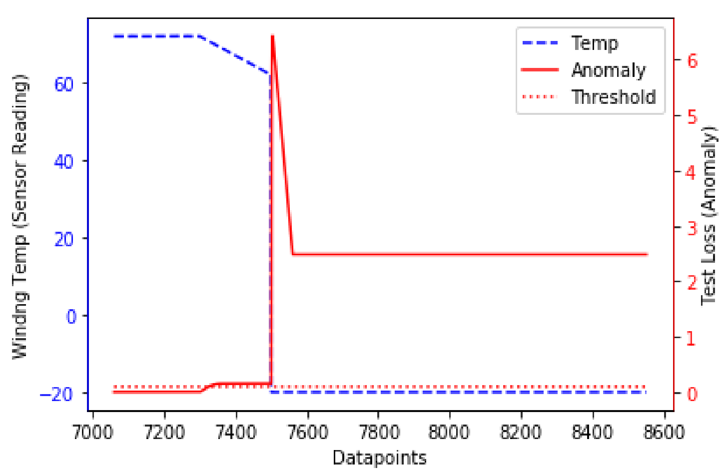

Ramp Falling Data vs Fault
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Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

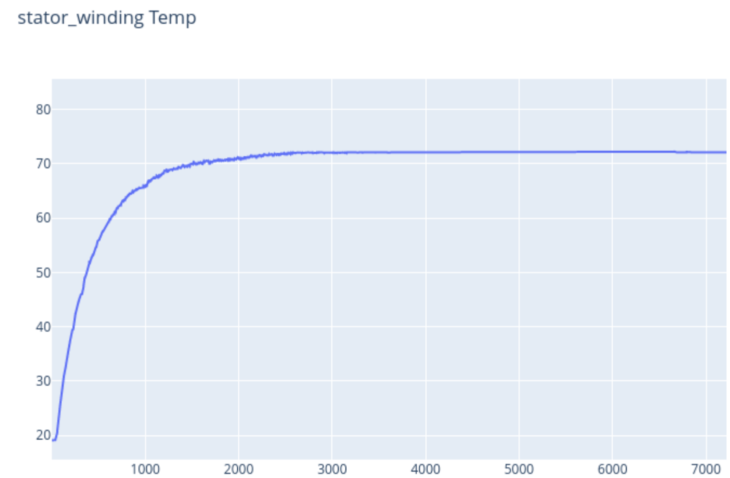
Part B (LSTM Timesteps>Error Window)

3. Data Vs Anomaly Plots Configuration:

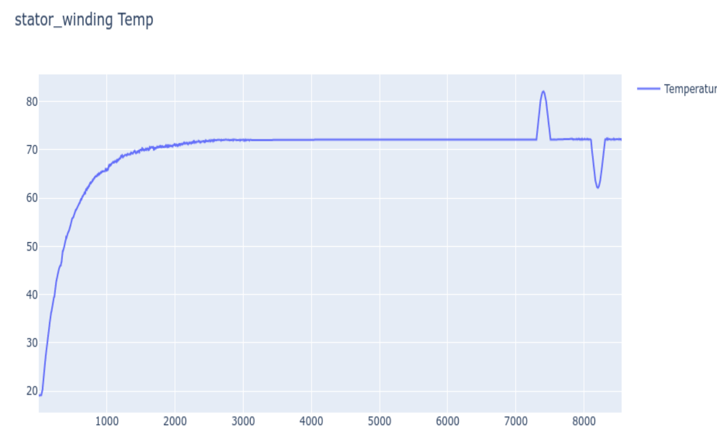
- Dataset: EV stator winding Temp. vs Time (0.5 sec per datapoint)
- LSTM timesteps: 300 data points
- Epochs = 50 ; Batch Size = 60
- Error window: 200 data points
- Error injected as Sine, Square & Ramp wave
- Error injected as both Positive and Negative values in +Y axis

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

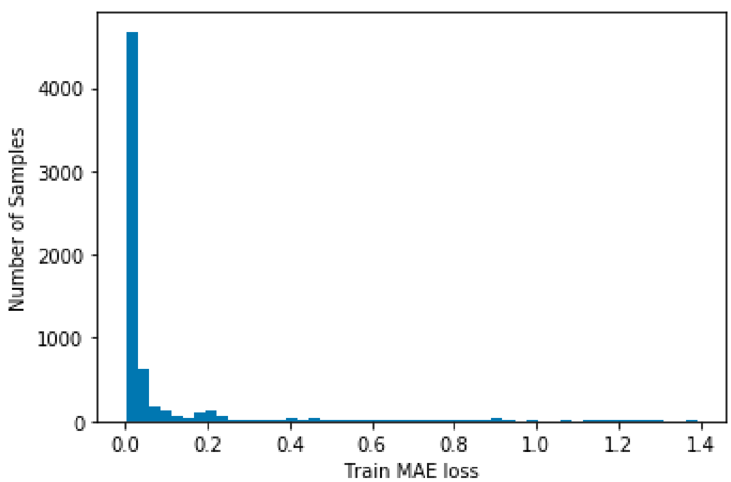
3.1 Sine Waveform error



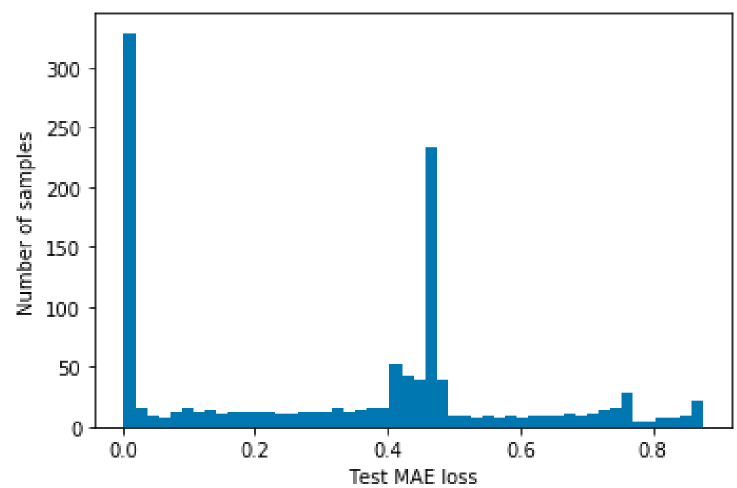
Training Dataset



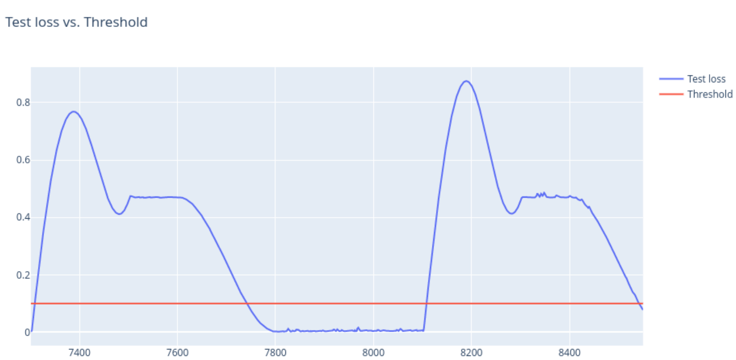
Sine Dataset



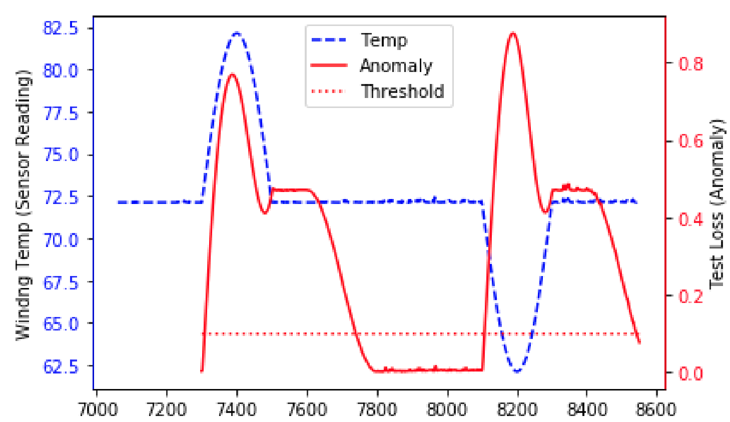
Sine Train MAE loss



Sine Test MAE loss



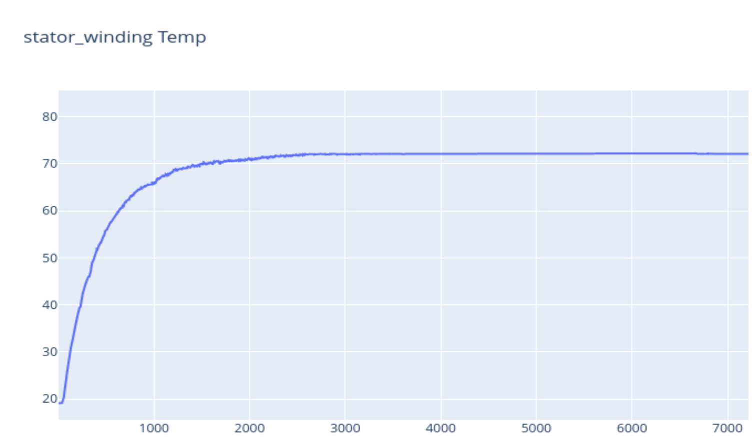
Sine Anomaly vs Threshold



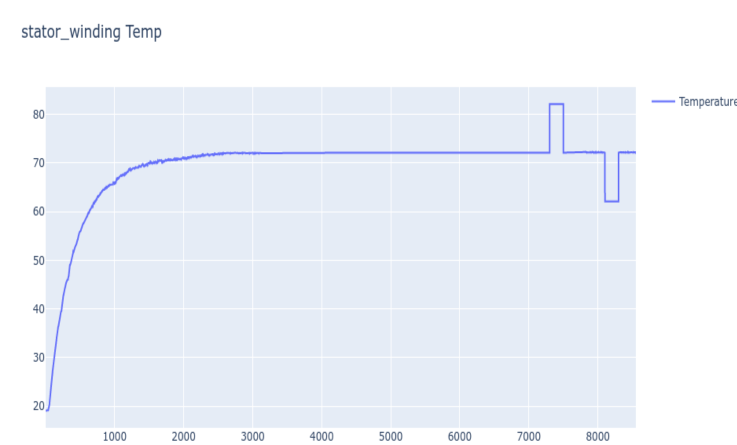
Sine Data vs Anomaly

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

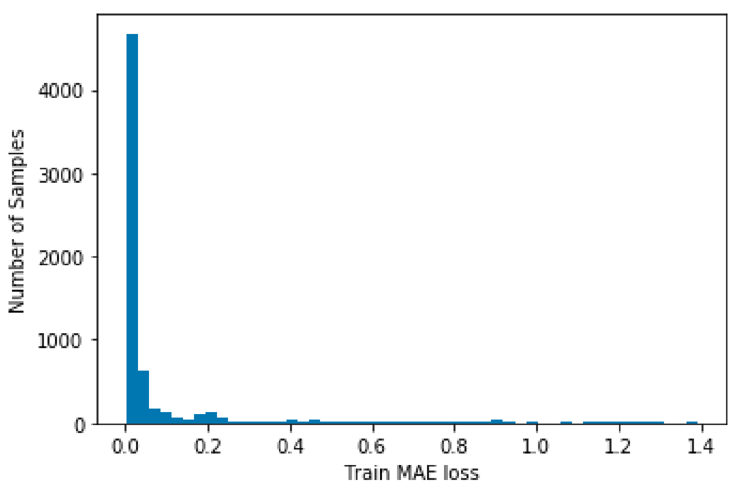
3.2 Square Waveform error



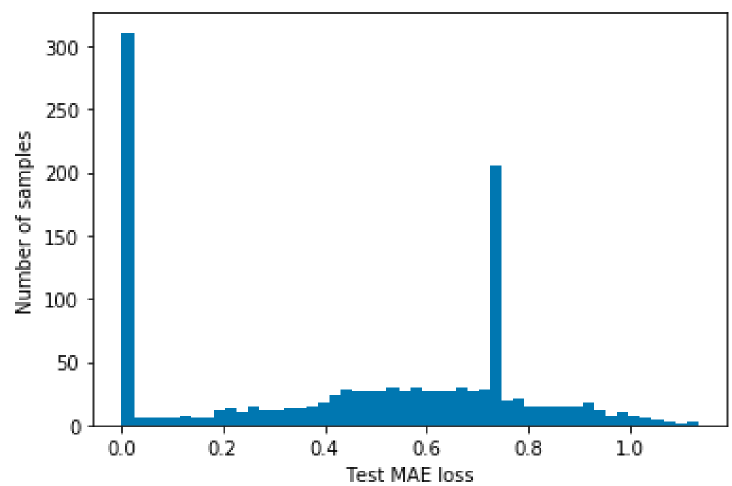
Training Dataset



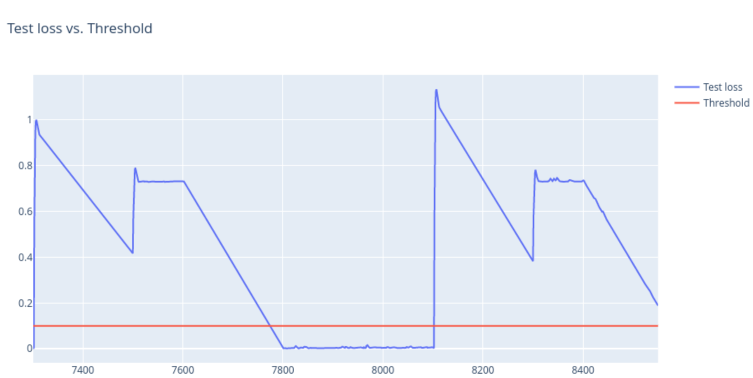
Square Dataset



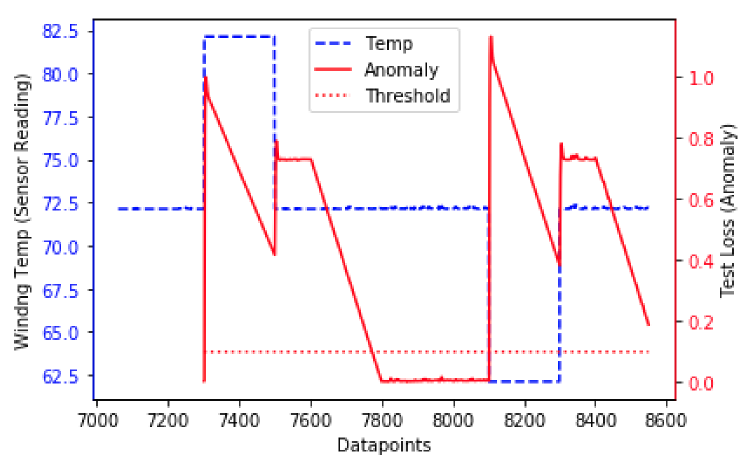
Square Train MAE loss



Square Test MAE loss



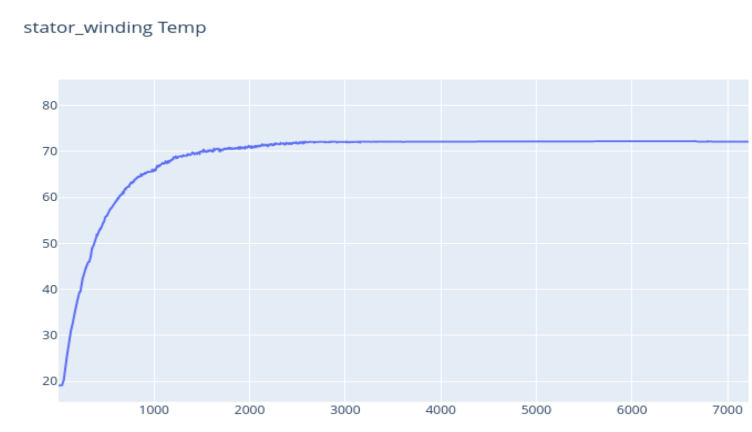
Square Anomaly vs Threshold



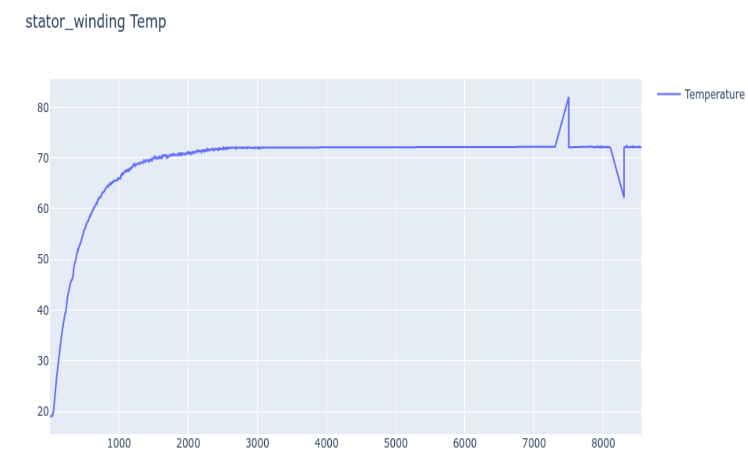
Square Data vs Anomaly

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

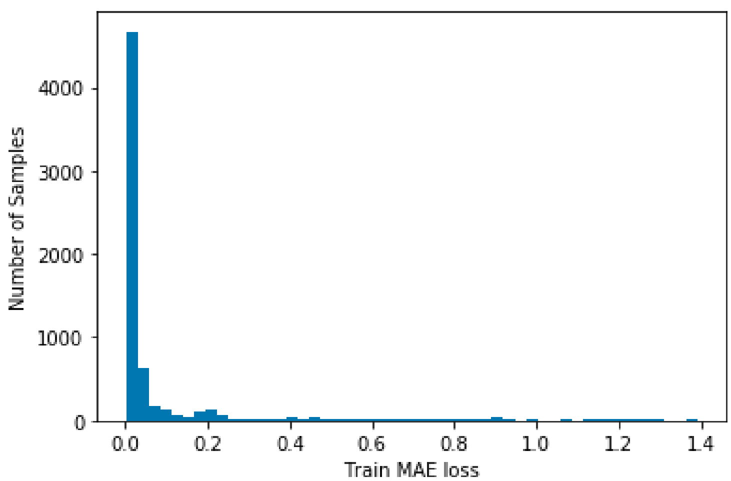
3.3 Ramp Waveform error



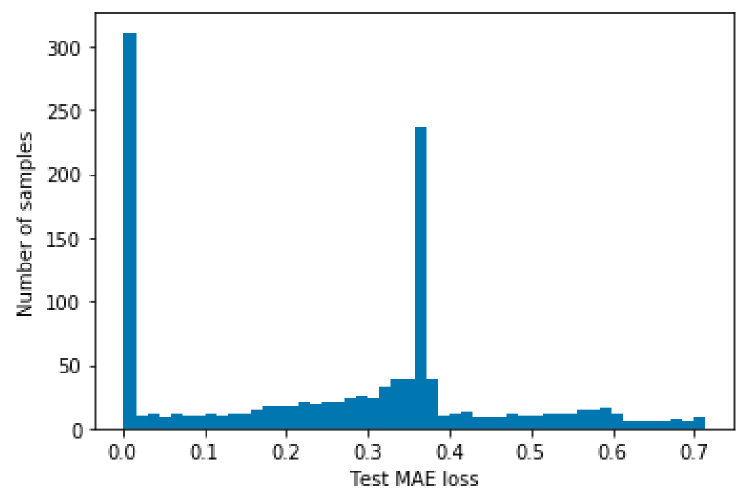
Training Dataset



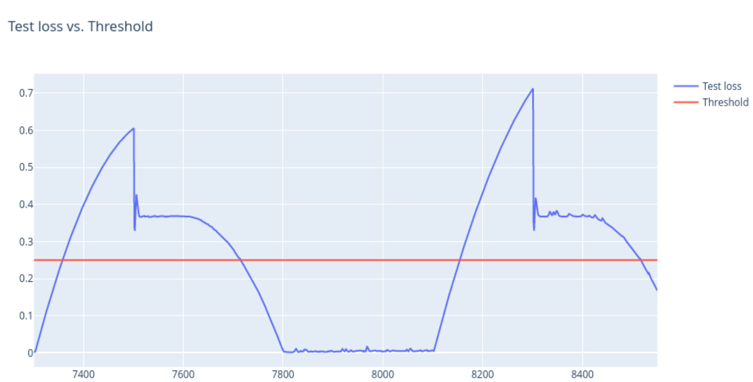
Ramp Dataset



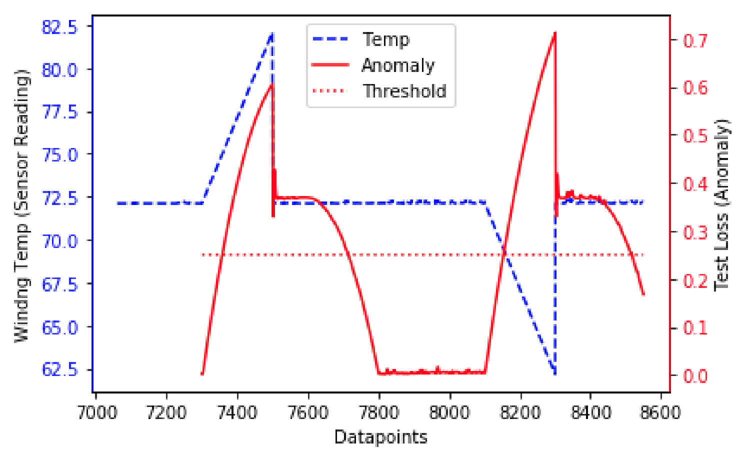
Ramp Train MAE loss



Ramp Test MAE loss



Ramp Anomaly vs Threshold



Ramp Data vs Anomaly

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

4. Data Vs Fault Plots

Configuration:

- Dataset: EV stator winding Temp. vs Time (0.5 sec per datapoint)
- LSTM window: 300 data points
- Epochs = 50 ; Batch Size = 60
- Error window: 200 data points
- Error injected as Sine, Square & Ramp wave
- Error injected as Positive and Negative values in +Y axis separately
- Operating range of the sensor is assumed from 0*C to 100*C,
- When the sensor is faulty, it will send the temp. that is beyond the operating range, i.e. -20*C and 120*C

<table>
<tr><th colspan="2">4.1.1 Sine, Fault HIGH</th></tr>
<tr><th>Sine Error curve: Rising</th><th>Sine Error curve: Falling</th></tr>
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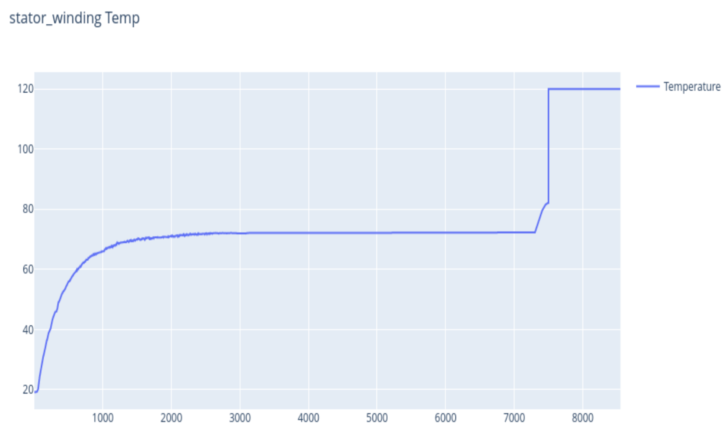

Sine Dataset
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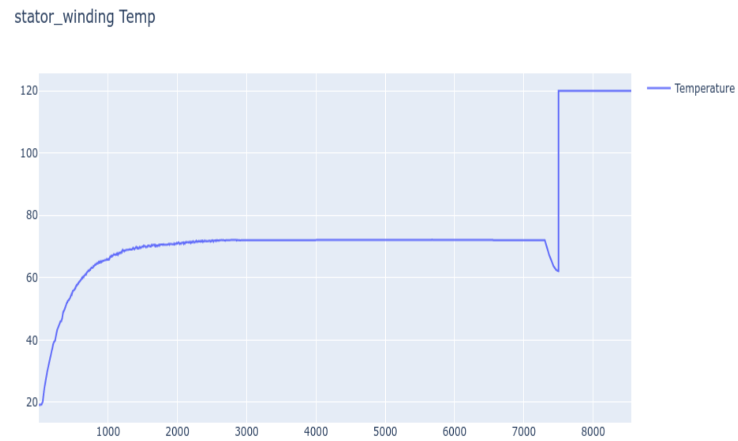

Sine Dataset
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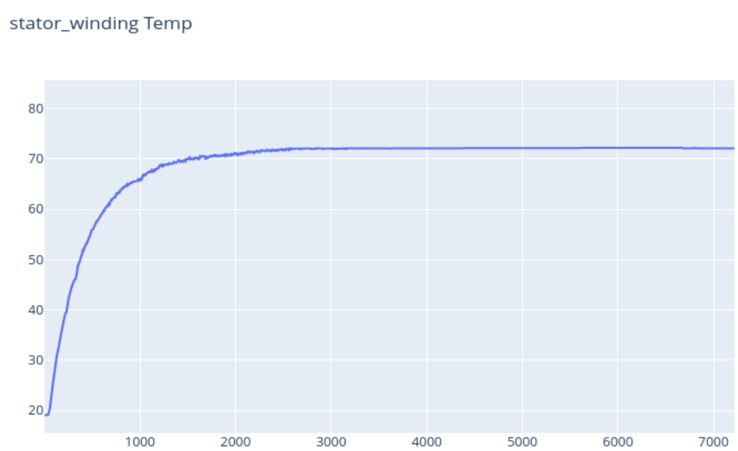

Training Dataset
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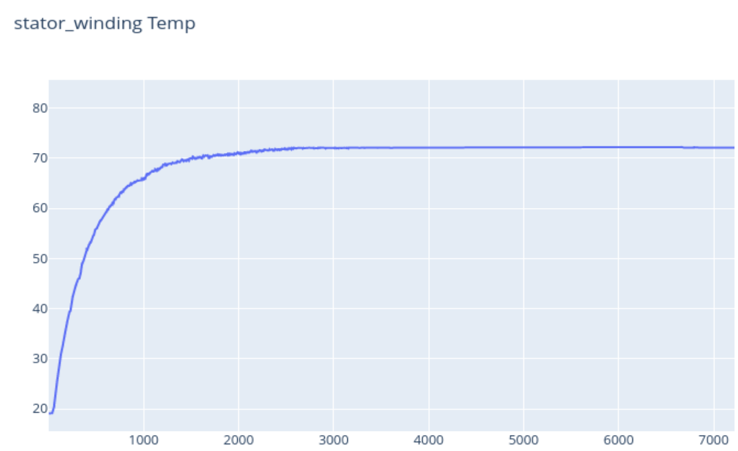

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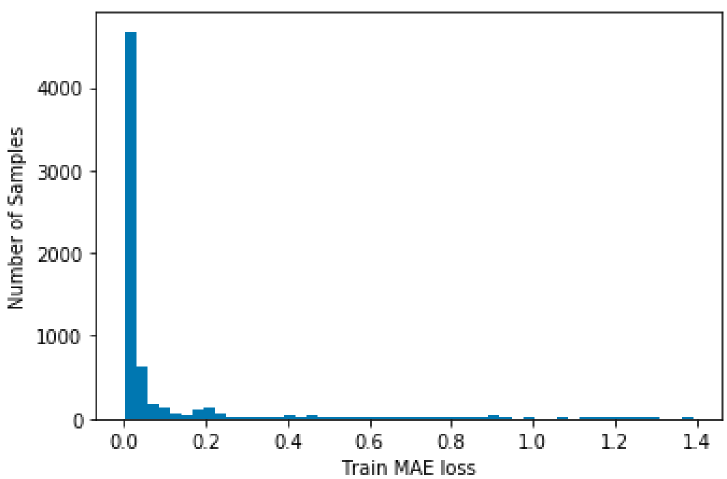

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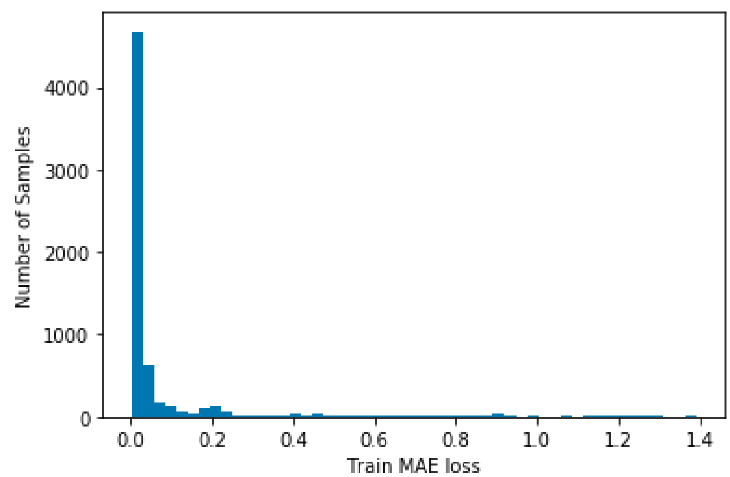

Train MAE loss
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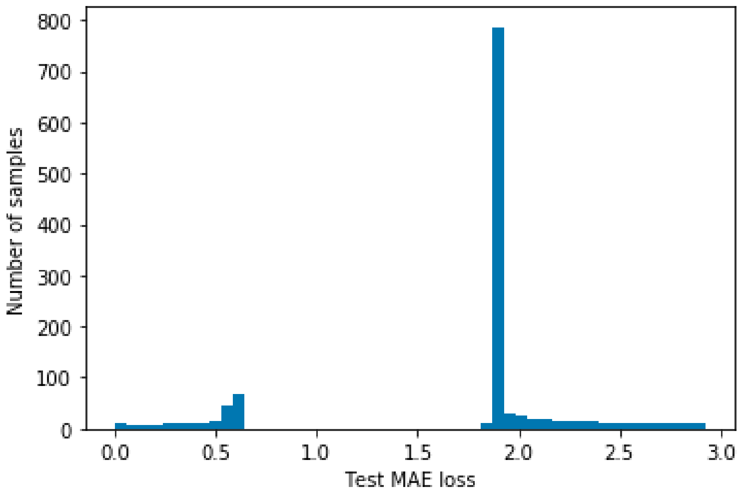
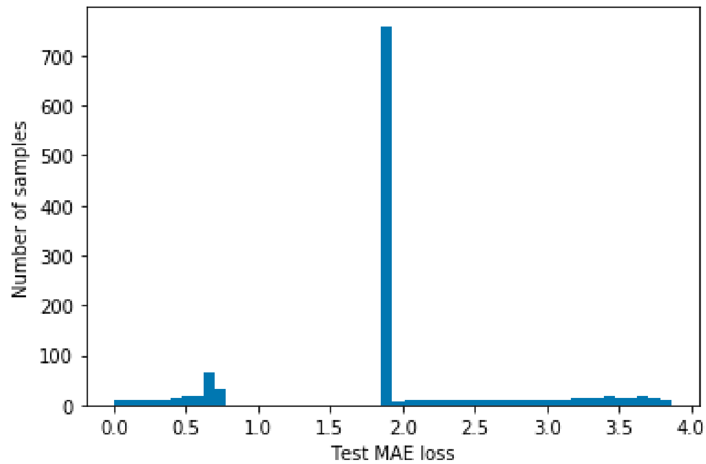
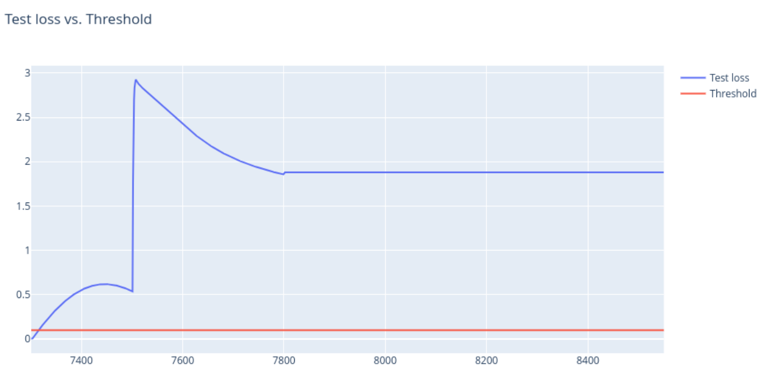
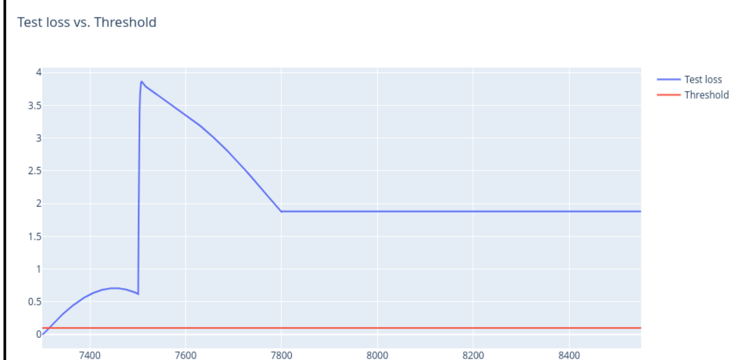
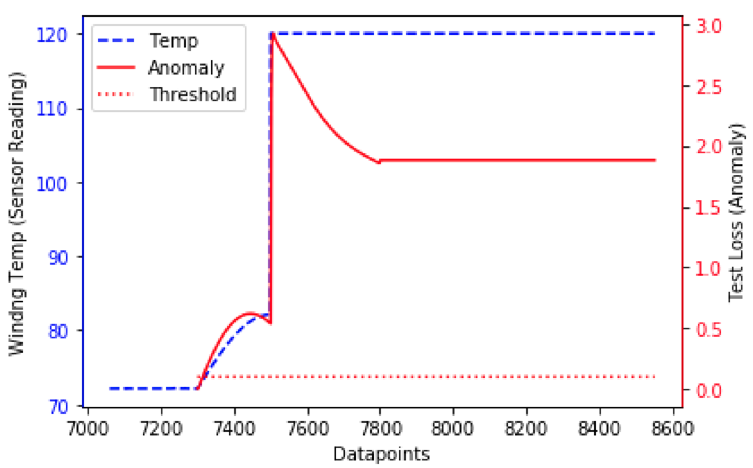
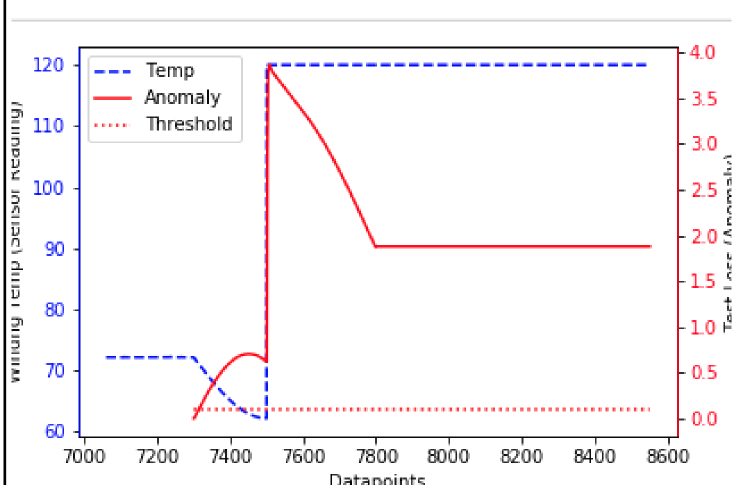
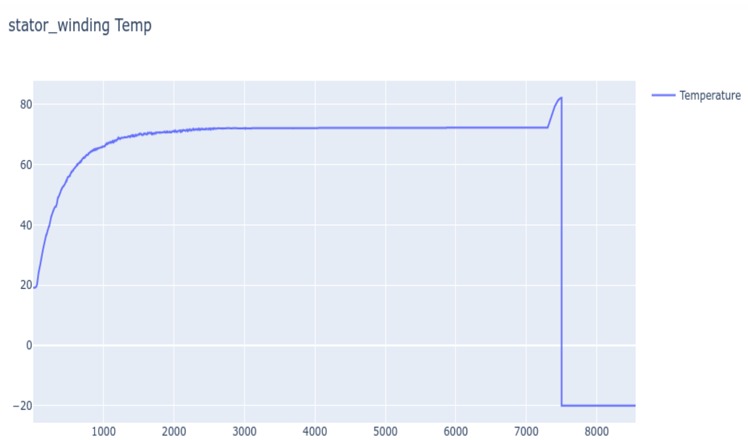
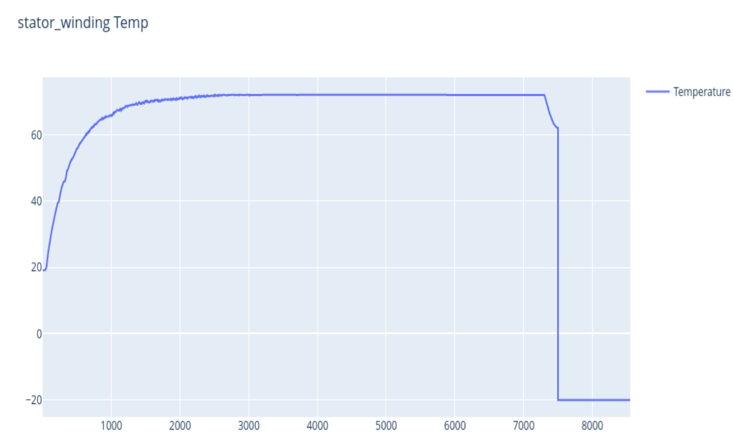
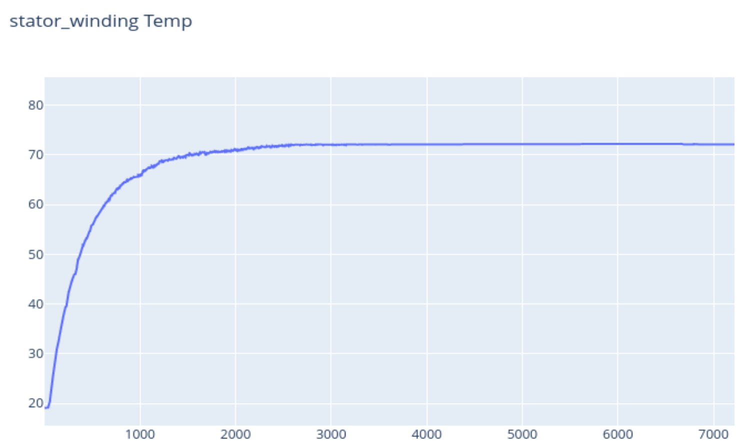
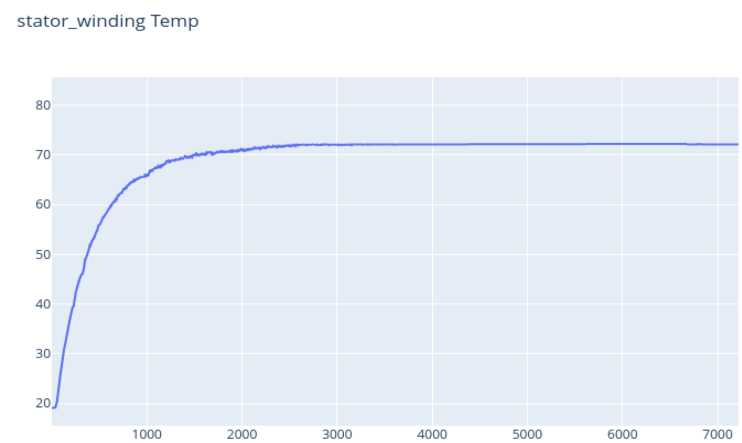
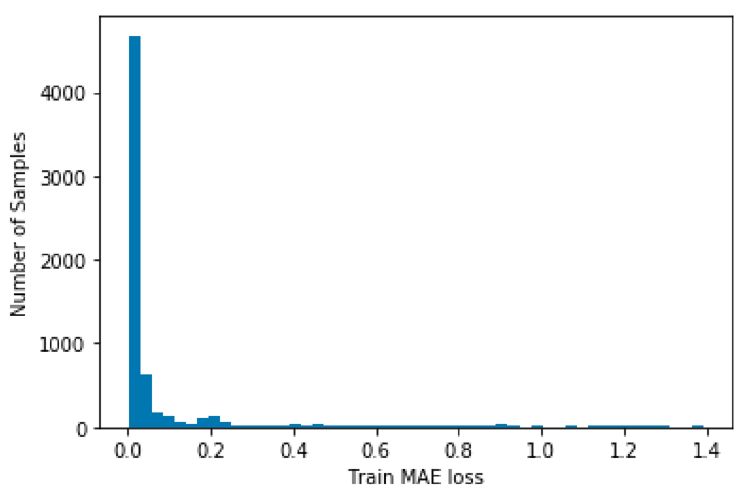
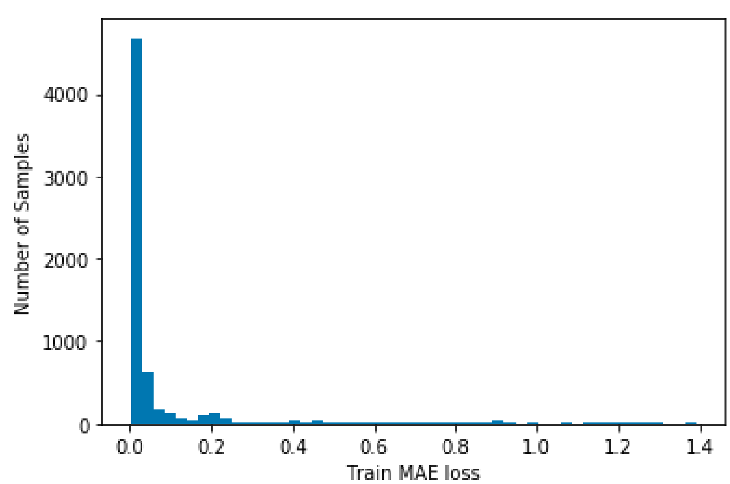
Sine Error curve: Rising	Sine Error curve: Falling
 Sine Test MAE loss	 Sine Test MAE loss
 Sine Anomaly vs Fault	 Sine Anomaly vs Fault
 Sine Rising Data vs Fault	 Sine Falling Data vs Fault

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

4.1.2 Sine, Fault LOW	
Sine Error curve: Rising	**Sine Error curve: Falling**
 Sine Dataset	 Sine Dataset
 Training Dataset	 Training Dataset
 Train MAE loss	 Train MAE loss

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

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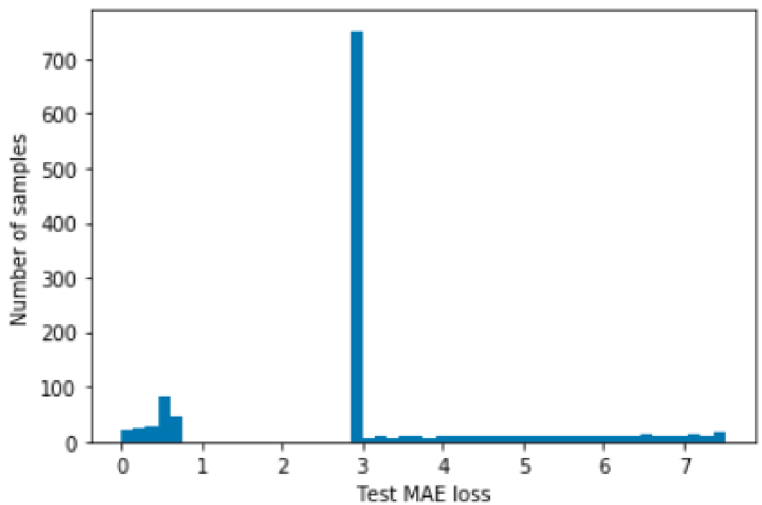

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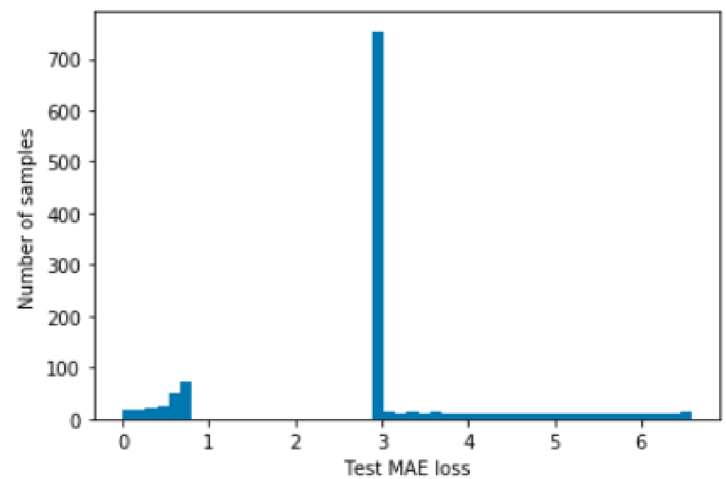

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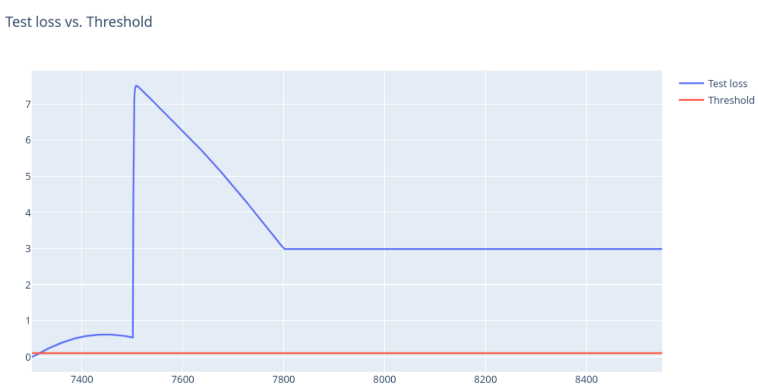

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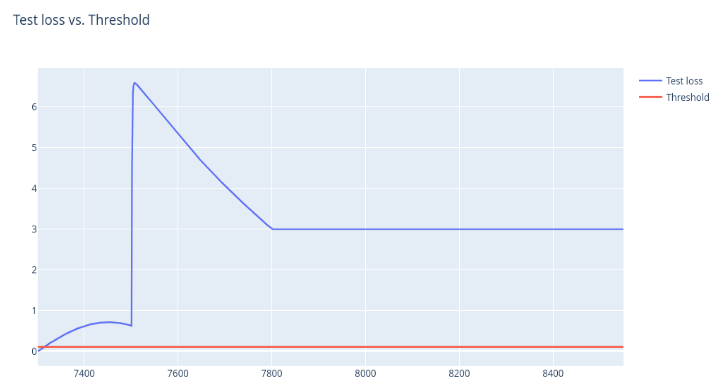

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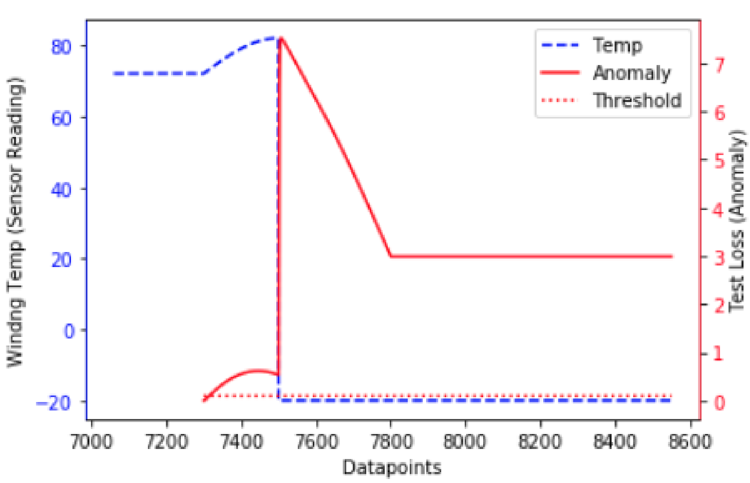

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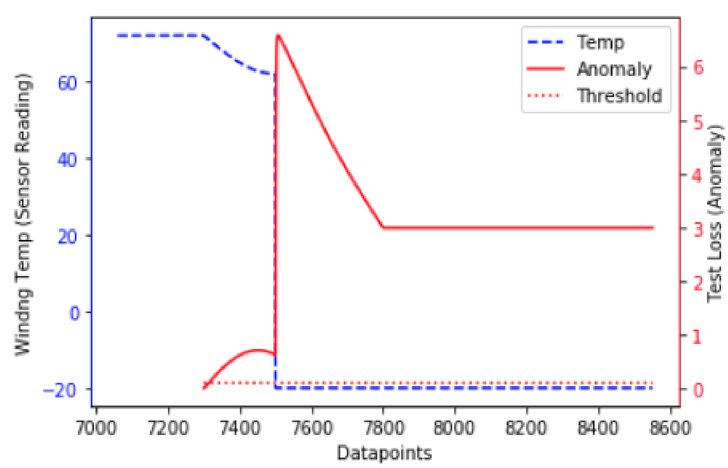

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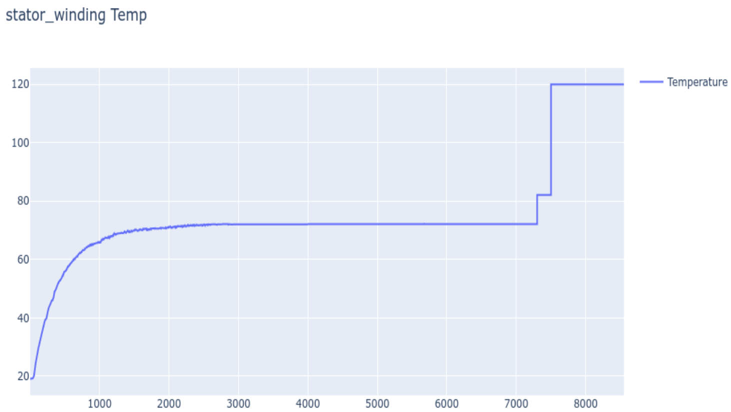
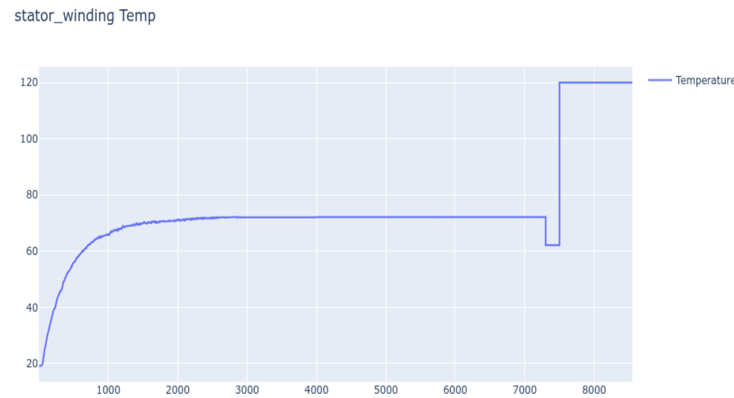
<tr><td>
Square Dataset</td><td>
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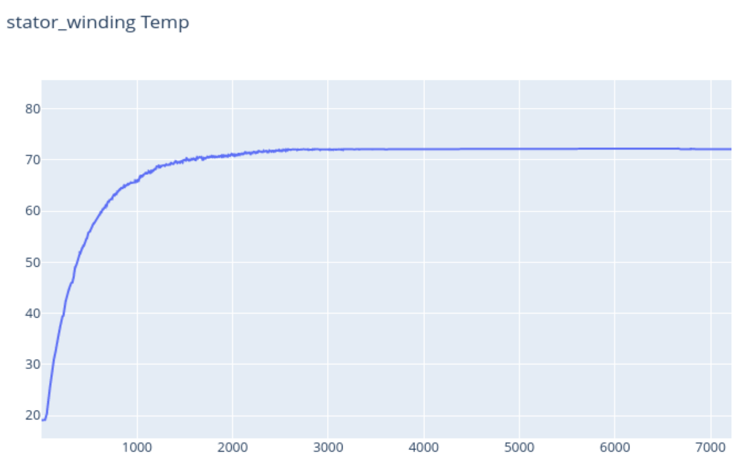
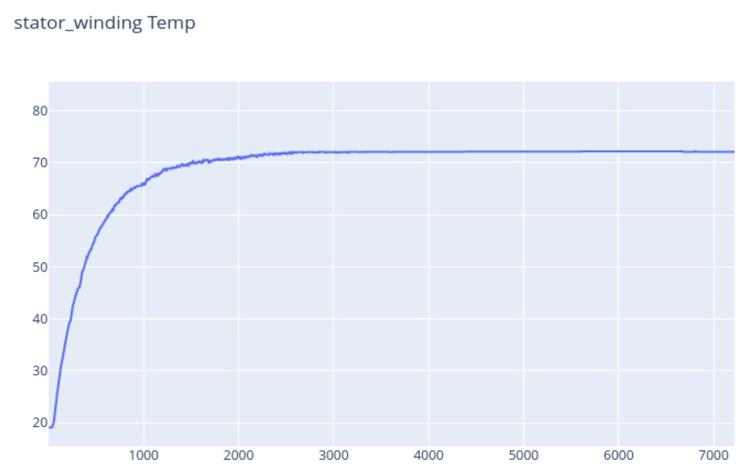
<tr><td>
Training Dataset</td><td>
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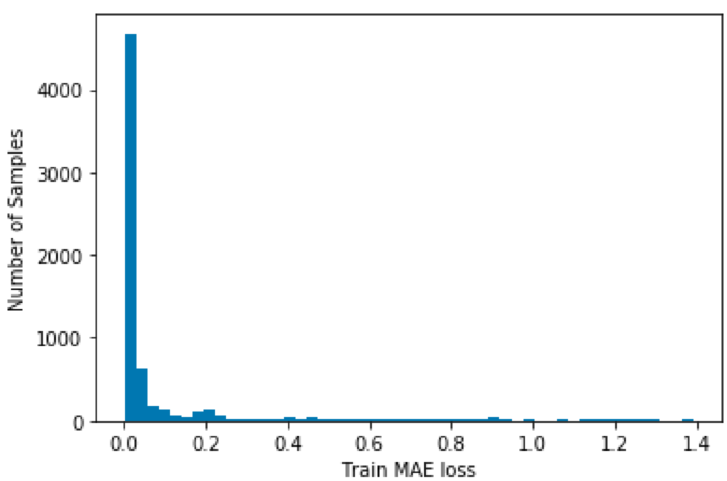
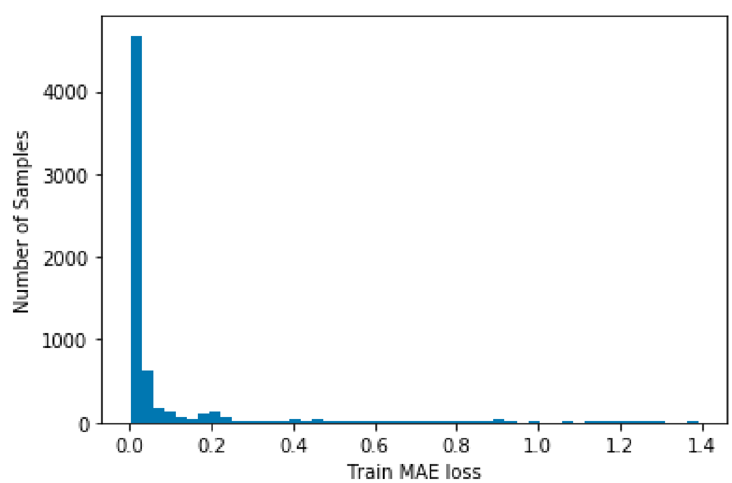
<tr><td>
Train MAE loss</td><td>
Train MAE loss</td></tr>
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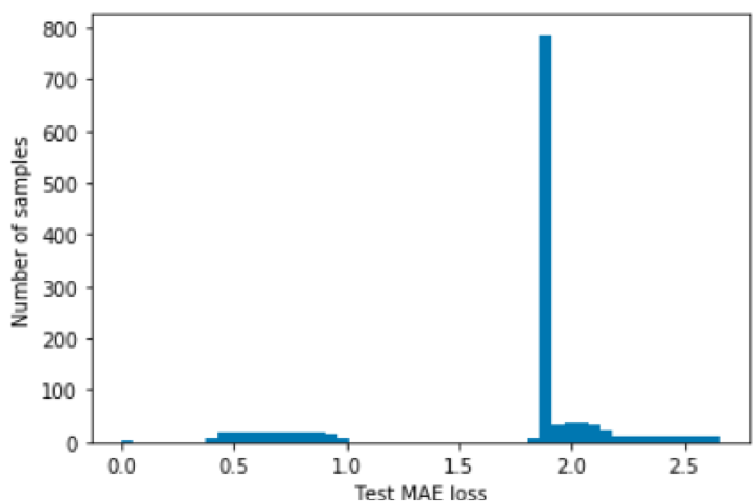
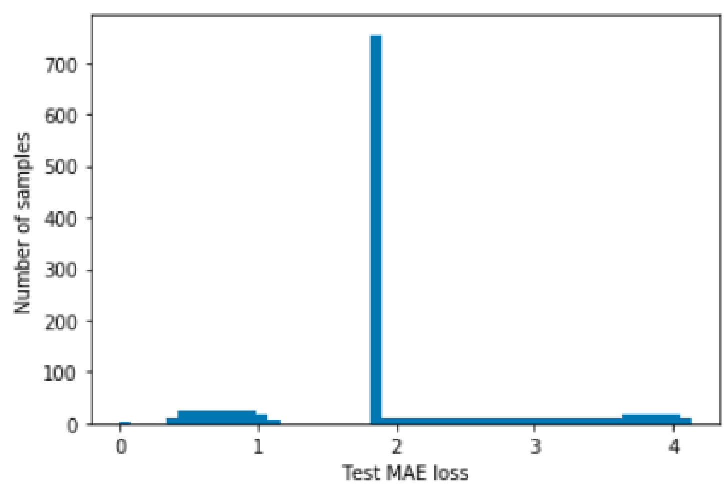
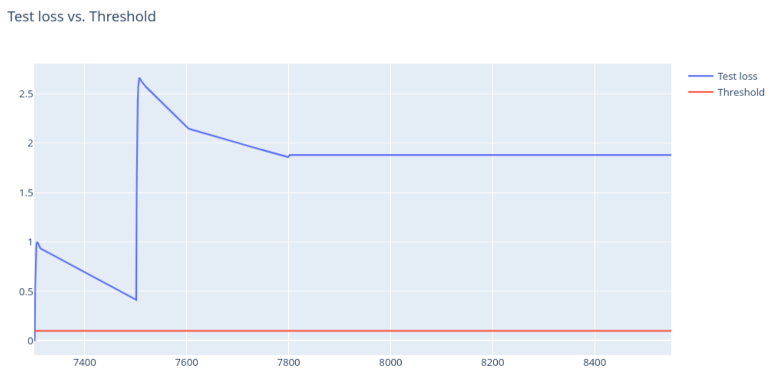
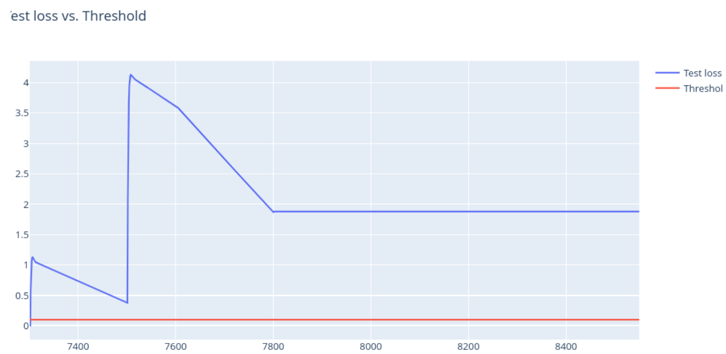
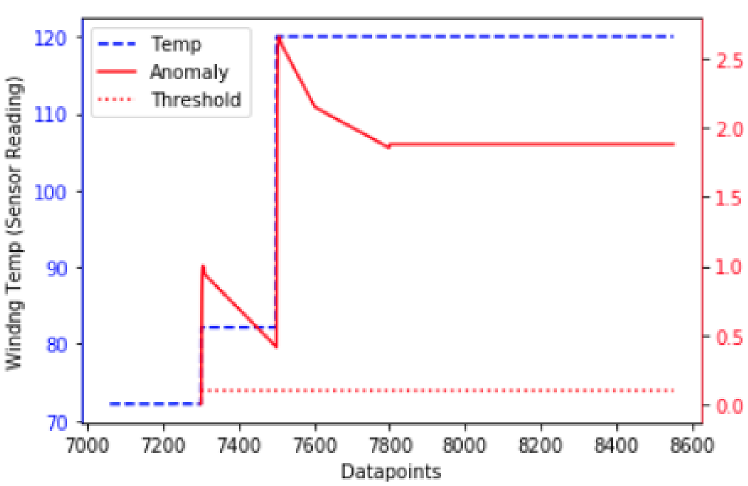
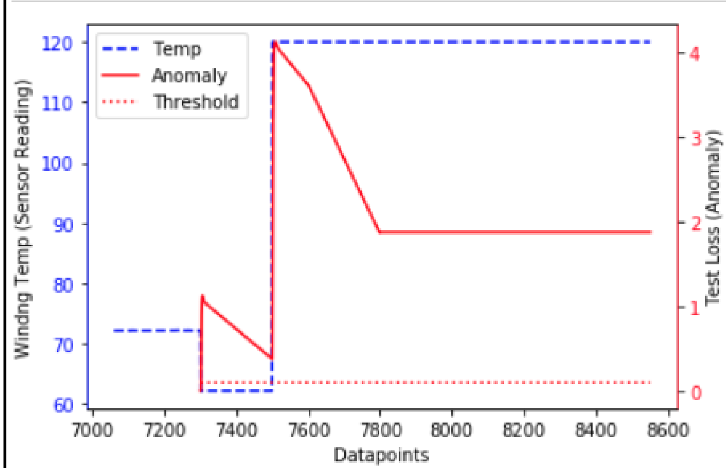
 Square Test MAE loss	 Square Test MAE loss
 Square Anomaly vs Fault	 Square Anomaly vs Fault
 Square Rising Data vs Fault	 Square Falling Data vs Fault

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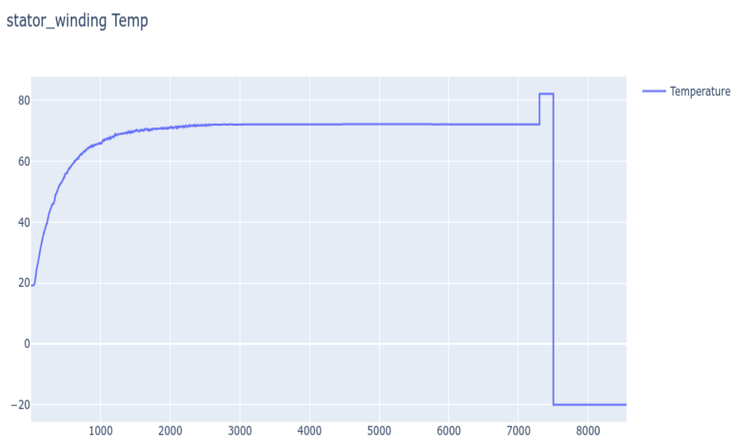

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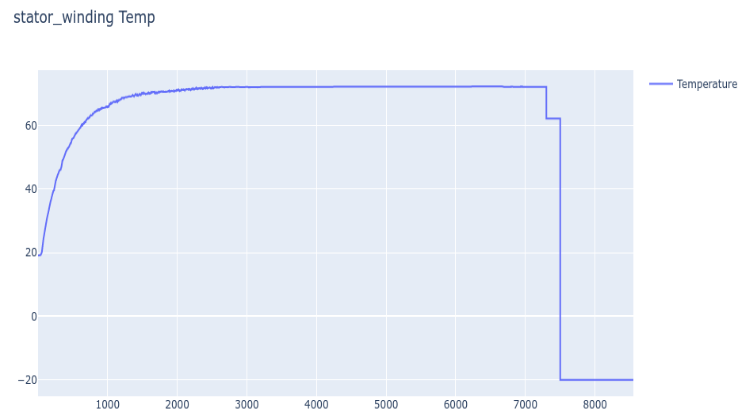

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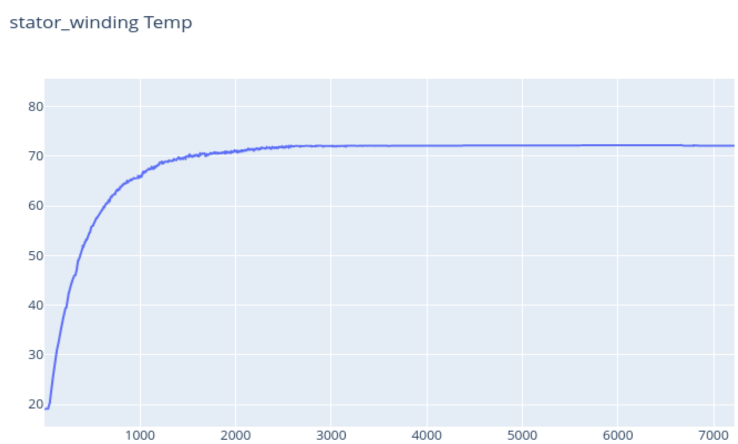

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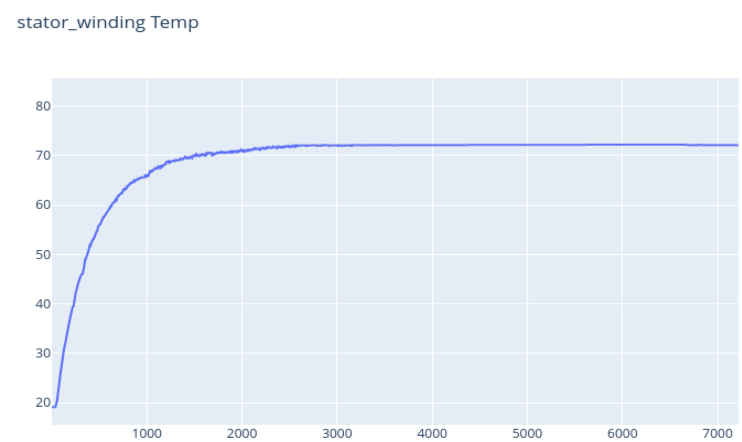

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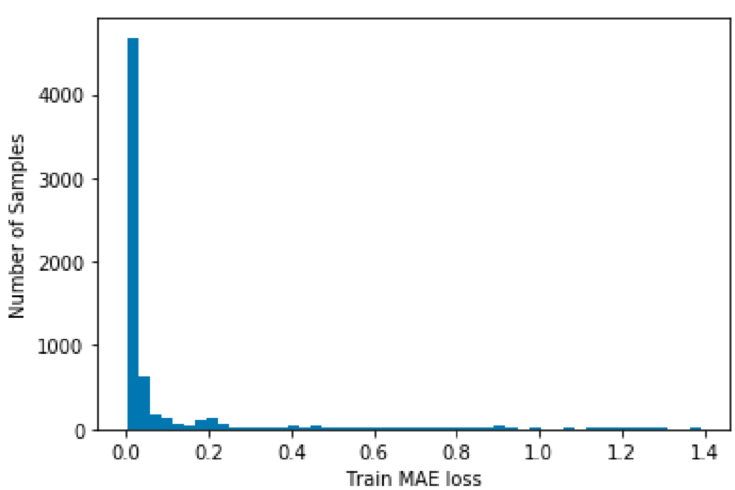

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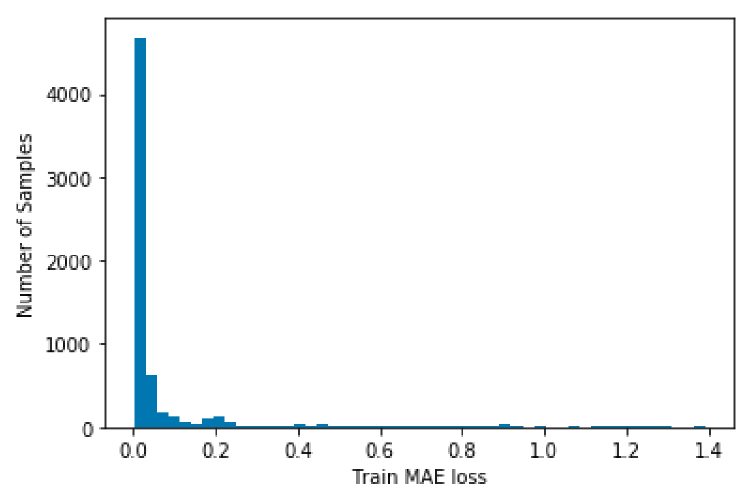

Train MAE loss
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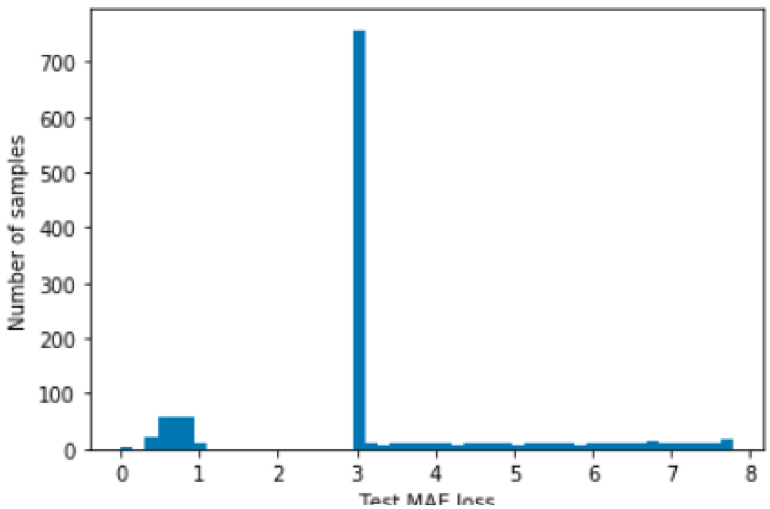
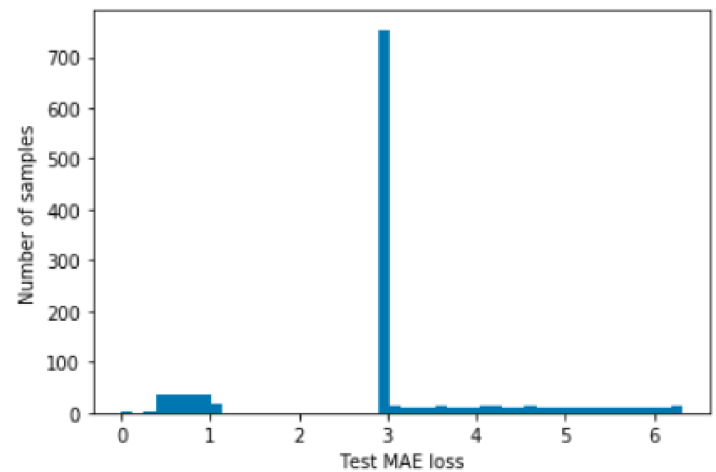
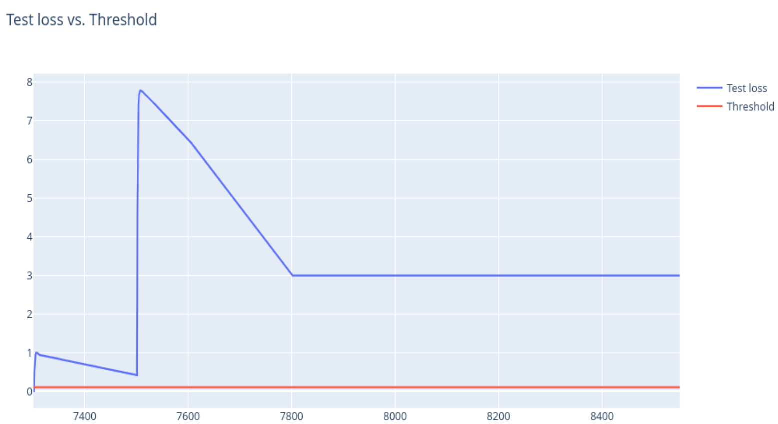
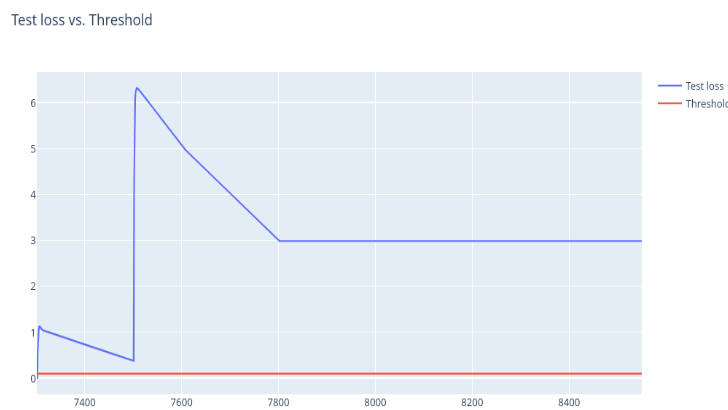
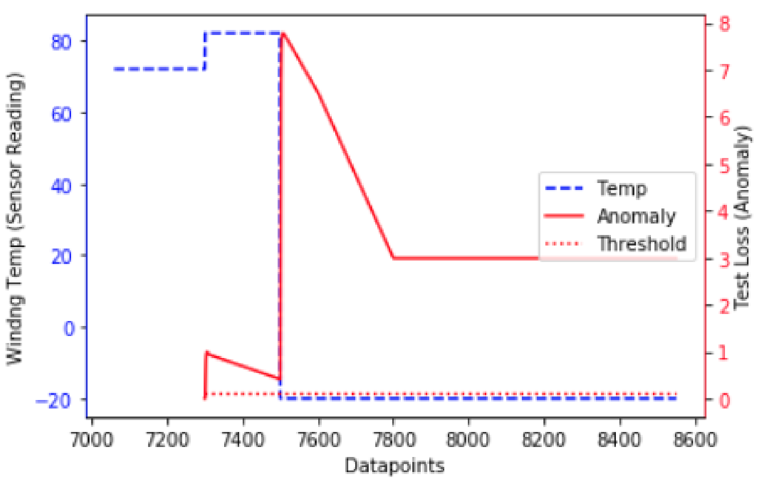
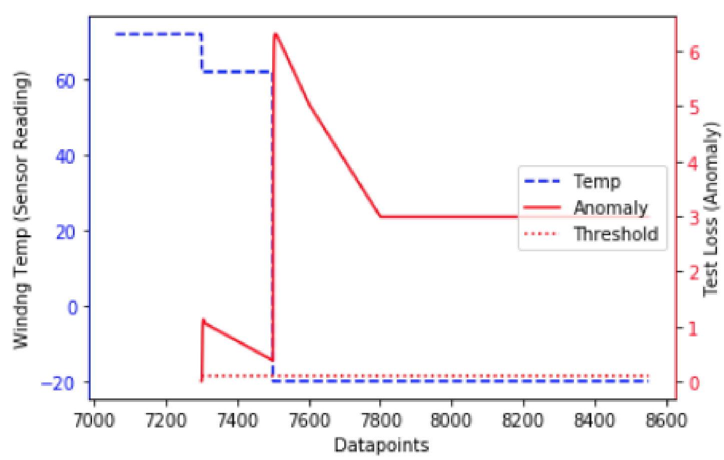
 Square Test MAE loss	 Square Test MAE loss
 Square Anomaly vs Fault	 Square Anomaly vs Fault
 Square Rising Data vs Fault	 Square Falling Data vs Fault

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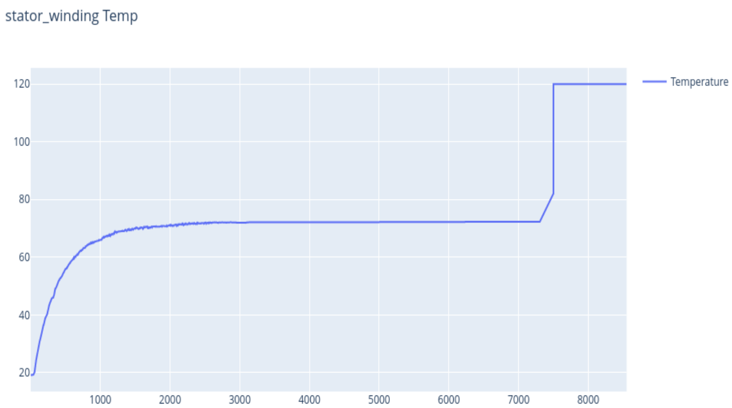
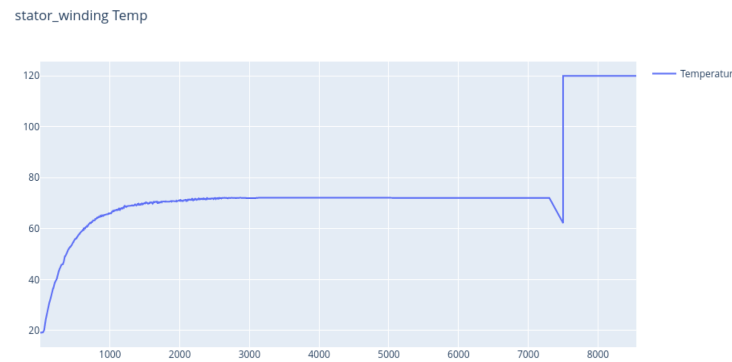
<tr><td>

Ramp Dataset</td><td>

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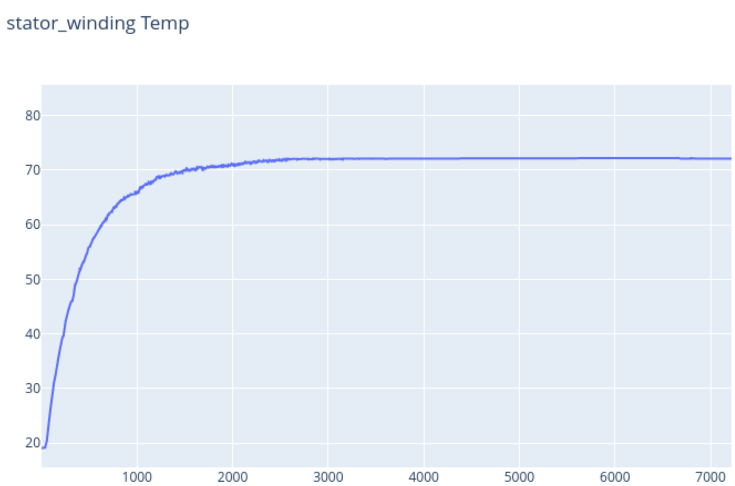
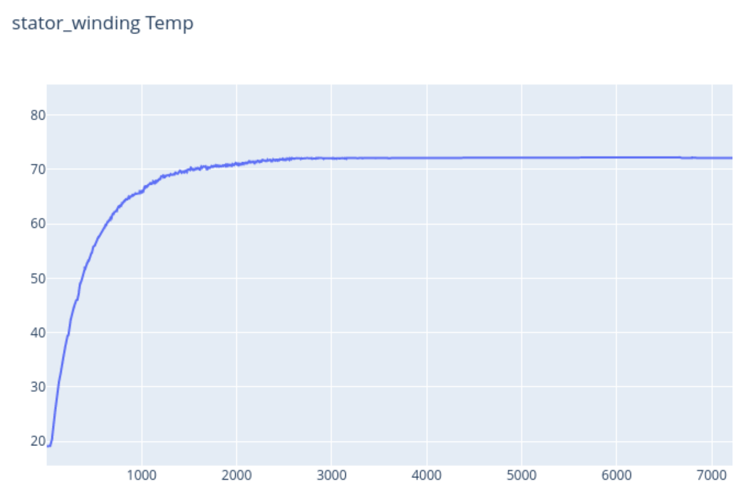
<tr><td>

Training Dataset</td><td>

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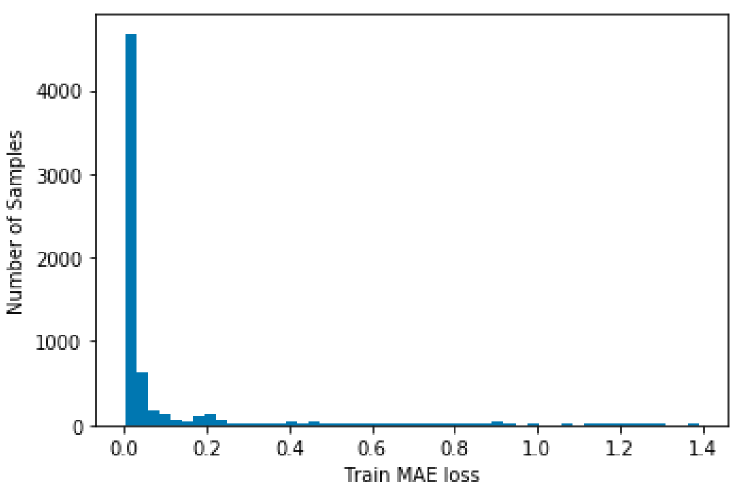
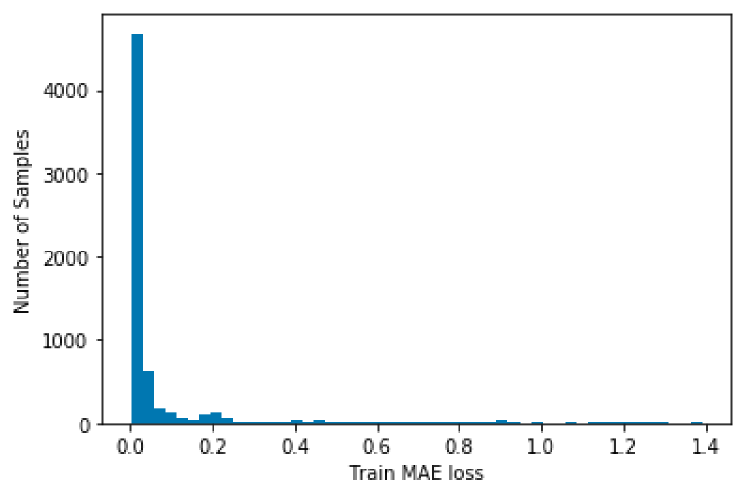
<tr><td>

Train MAE loss</td><td>

Train MAE loss</td></tr>
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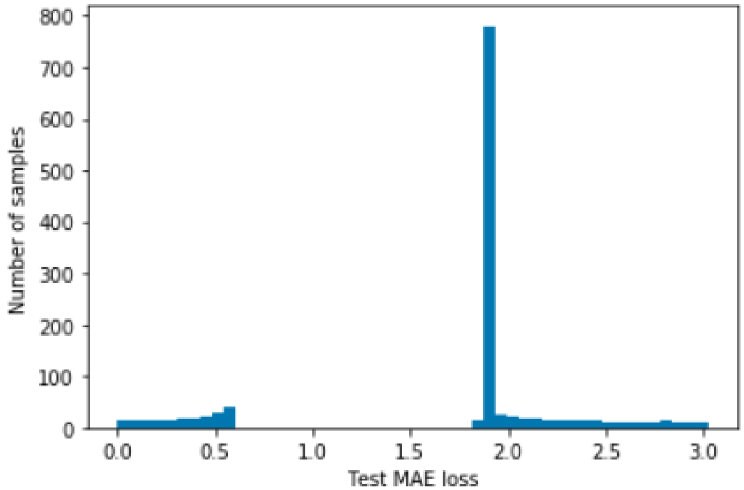
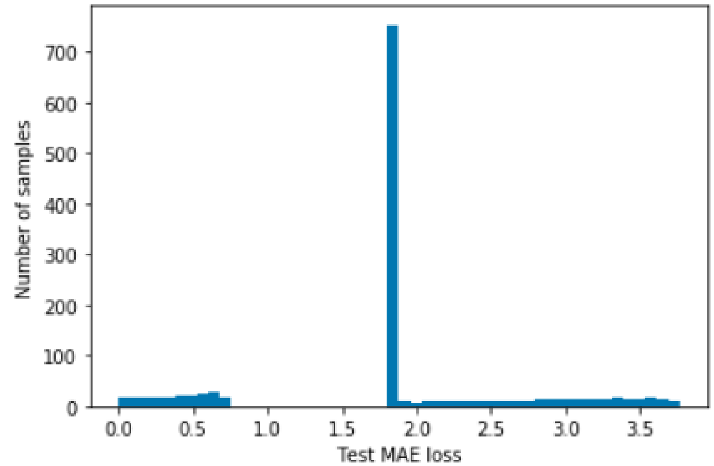
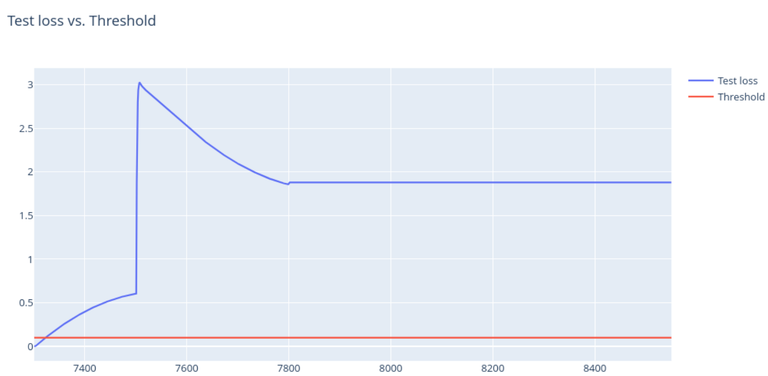
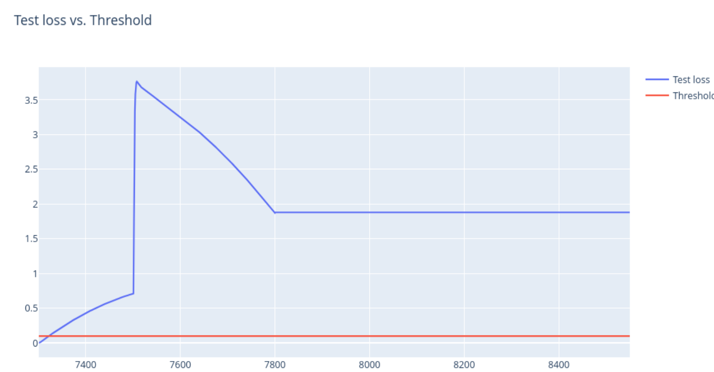
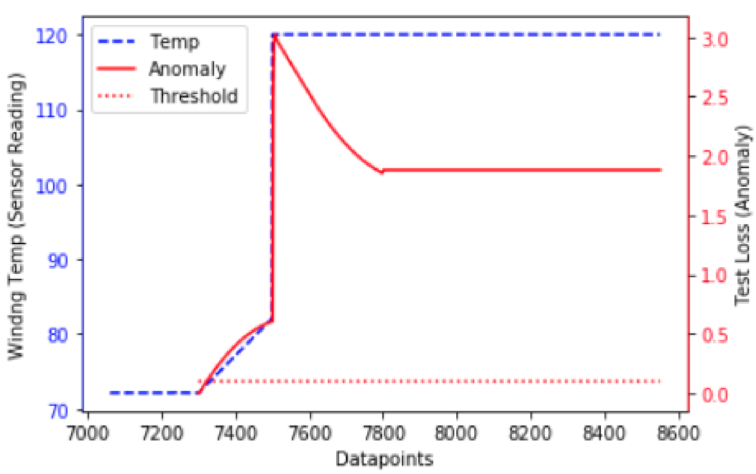
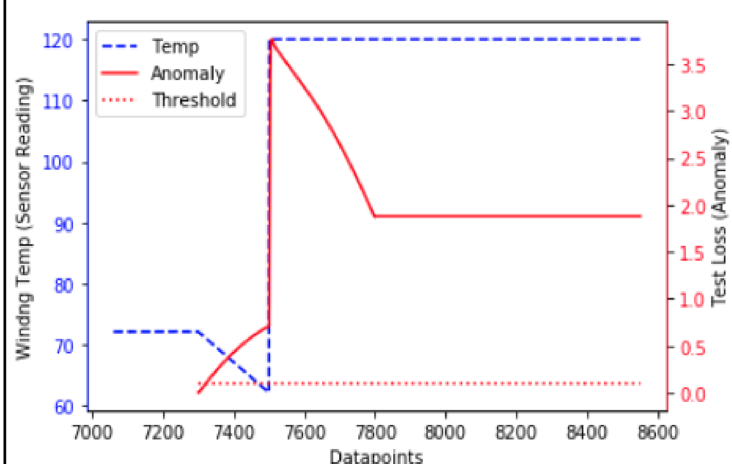
 Ramp Test MAE loss	 Ramp Test MAE loss
 Ramp Anomaly vs Fault	 Ramp Anomaly vs Fault
 Ramp Rising Data vs Fault	 Ramp Falling Data vs Fault

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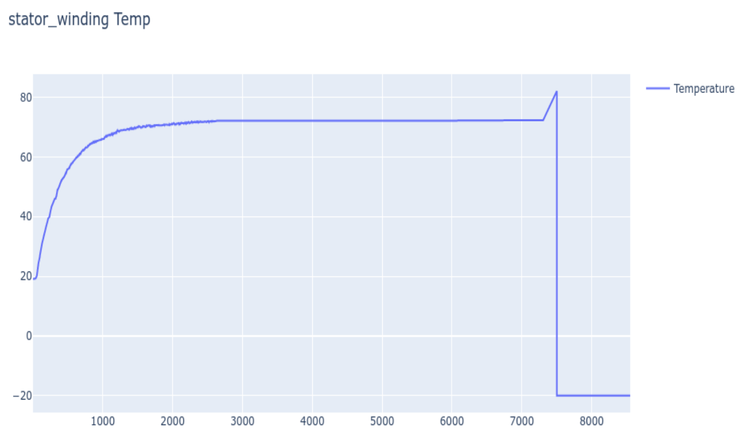
<td>

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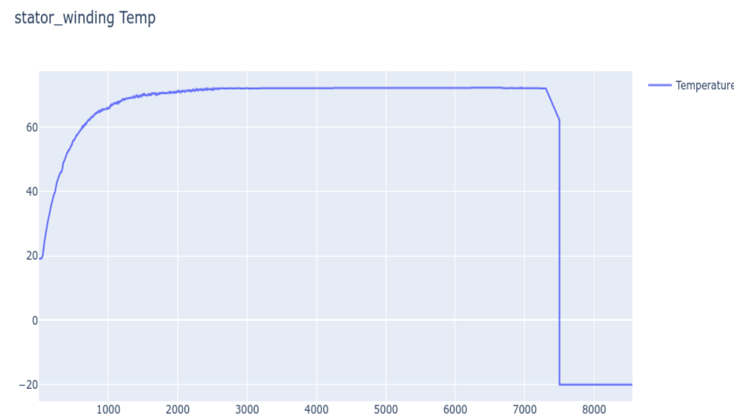
<td>

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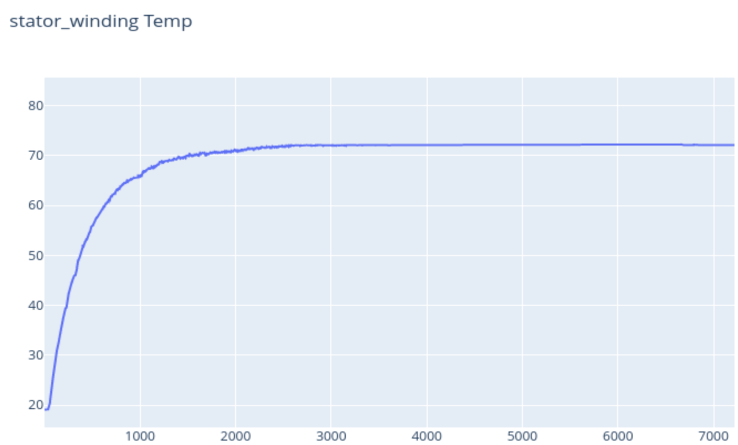
<td>

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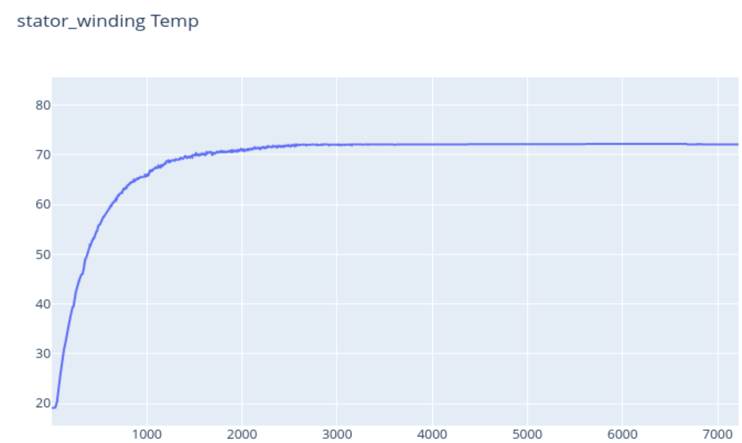
<td>

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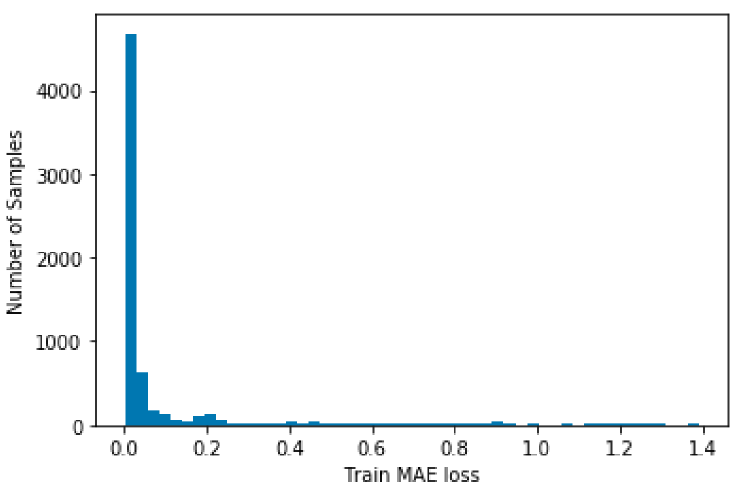
<td>

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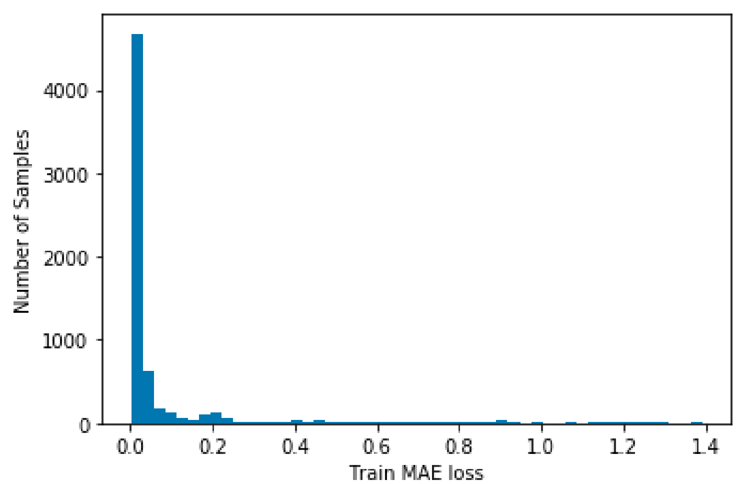
<td>

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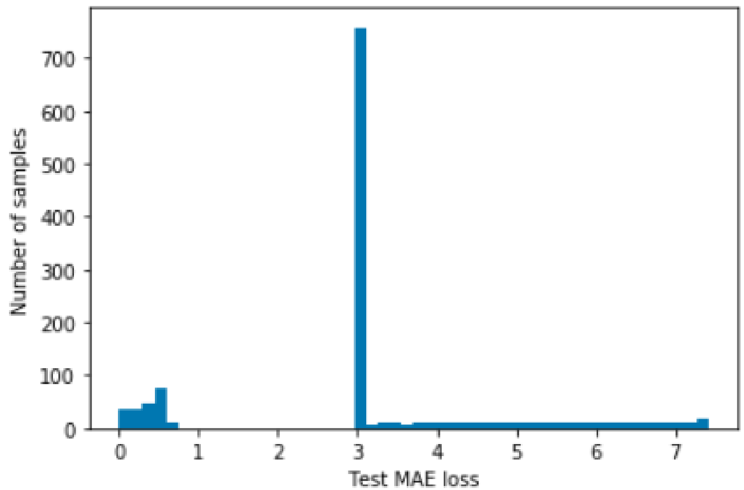
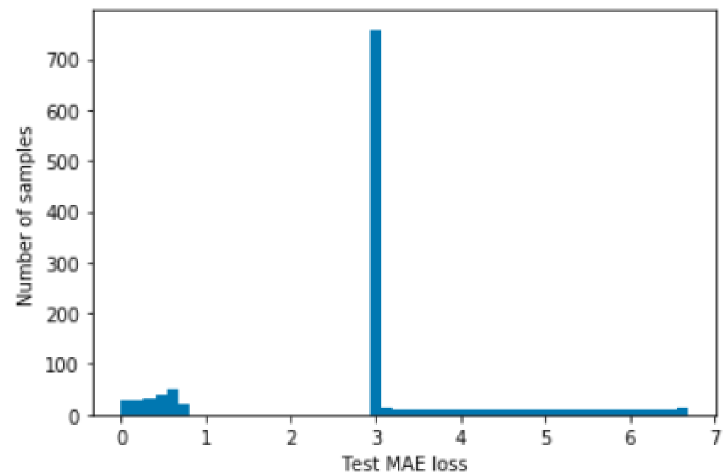
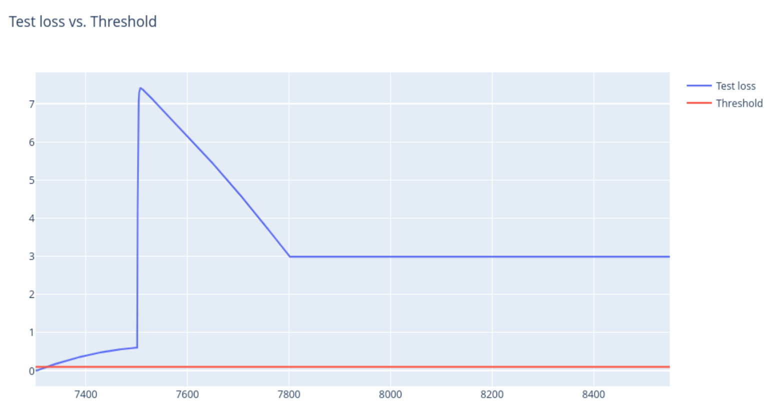
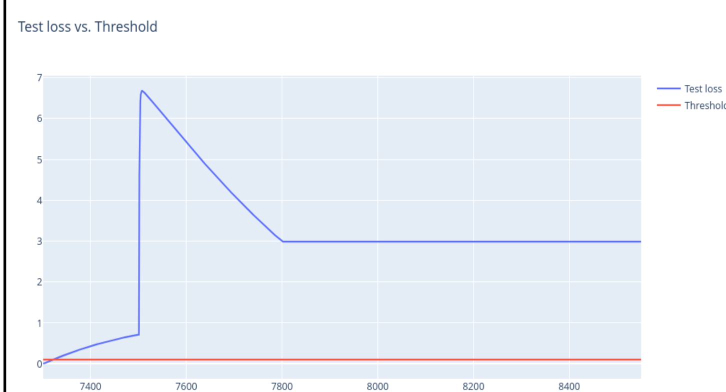
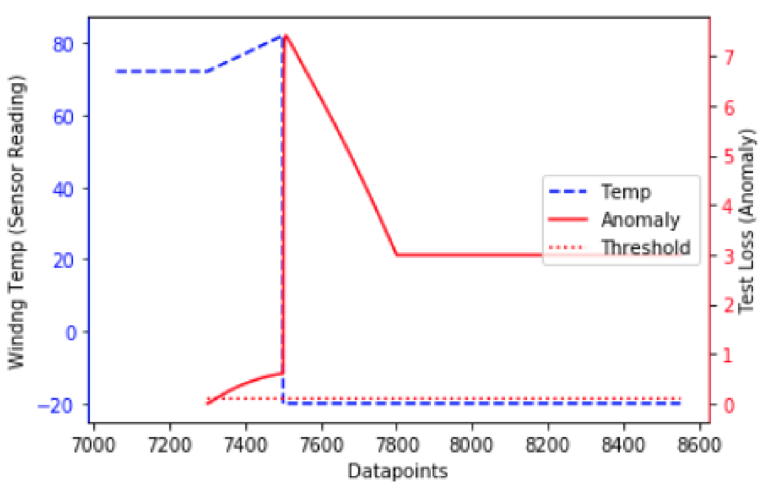
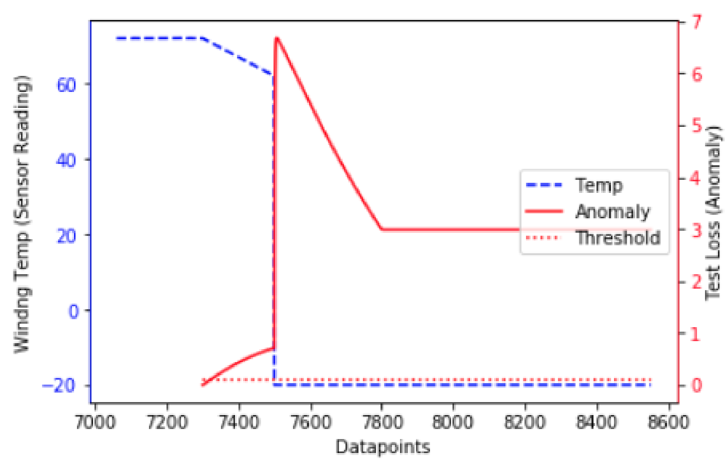
 Ramp Test MAE loss	 Ramp Test MAE loss
 Ramp Anomaly vs Fault	 Ramp Anomaly vs Fault
 Ramp Rising Data vs Fault	 Ramp Falling Data vs Fault

Images: https://github.com/biplabro/Anomaly-Detection-LSTM-AutoEncoder/tree/master/Summary-Images

Observations:

- Increased LSTM window leads to **increased** training time
- In the larger LSTM timestep observation it is noticed that more time is needed for the model to report normal data back again, after the actual anomaly/ fault has been removed (Part-B; **Data vs Anomaly & Data vs Fault plots**)
- LSTM window detects the anomaly in the rising or falling trend of the error pattern.
- Most useful for detecting and confirming if there is an anomaly started or stopped
- Not much useful for calculating the degree of anomaly or how severe the anomaly is.
- LSTM window is specially useful & most effective in detecting the peak or sudden reversal of an error pattern while dealing with time series values.
- Shortetr timesteps are better for quick detection of anomalous / erroneous data. For this specific example, the data is considered received from industrial temperature sensors. Thus, **LSTM window of 30 to 60 seconds are more realistic because these sensors are physically designed to handle extreme measurements for a minute or two, without damaging the equipments**.