Anomaly Detection
in
Conditioning Procedures

CERN-OPEN-2022-010
16/02/2022

Author: Martin Hofmann-Wellenhof
Date: February 16, 2022
Rev.: alpha 1.0

Contents

1 Introduction **3**
1.1 Outline . . . 3

2 Experimental Setup and Dataset **4**
2.1 Experimental Setup . . . 4
2.2 Comparison of the Datasets . . . 5

3 Preprocessing and Feature Extraction **7**
3.1 Preprocessing . . . 7
3.2 Feature Extraction . . . 10
3.3 Anomaly detection via LSTM autoencoder . . . 10

4 Analysis of potential anomalies in test case 2 **11**
4.1 TC2-anomaly cluster 11, 59, 61, 156 . . . 12
4.2 TC2-anomaly ramp-up 127 . . . 14
4.3 Analysis of potential anomalies in test case 3 . . . 16
4.3.1 TC3-anomaly ramp-up 72 . . . 17
4.3.2 TC3-anomaly ramp-up 42 . . . 17
4.3.3 TC3-anomaly cluster 26, 217, 261 - LSTM . . . 18

5 Conclusion **20**

1 Introduction

1.1 Outline

In this report, we summarize our approach to find anomalies in conditioning procedures with an LSTM autoencoder. We start off by outlining the experimental setup that was used by Pilan et al. [1] to create the dataset. Afterwards we describe the preprocessing we applied and how we extraceted features which we used to train the LSTM model. We then present the found anomalies and analyze them in more detail. At the end of the report we reiterate the main findings.
The code is provided on GitHub [2].

2 Experimental Setup and Dataset

The data we used for our analysis was taken from experiments on high DC voltage breakdown between stainless steel electrodes separated by long vacuum gaps conducted at the High Voltage Padova Test Facility [1]. Here we want to provide only a rough overview of the experiments to aid the understanding of our approach for anomaly detection. Therefore we will only focus on those parts of the original paper that are needed to understand our methodology. For a more detailed explanation of the experiments please refer to the original paper.

2.1 Experimental Setup

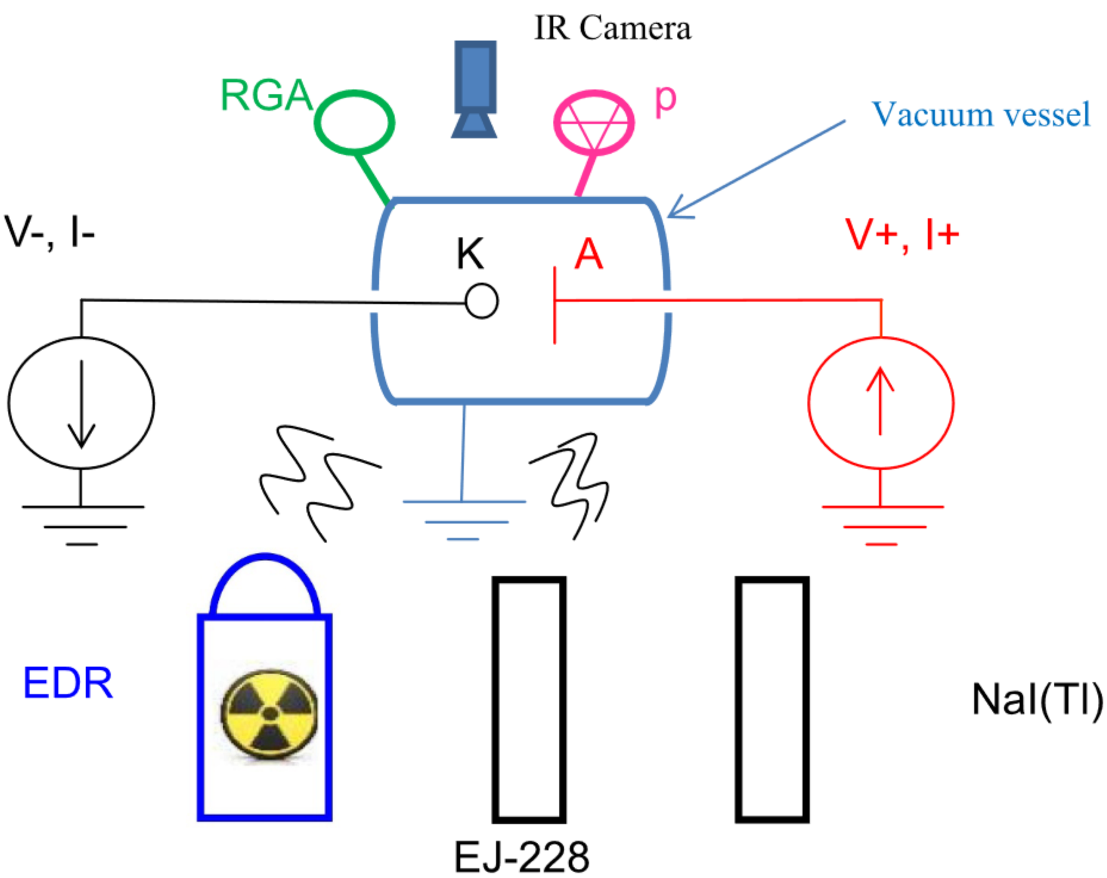

Figure 2.1: Experimental Setup scheme taken from page 4 of the original paper[1].

The experiment conducted is high voltage insulation across a gap in vacuum which is imported for the development of the electrostatic accelerator for the ITER neutral beam injector[1]. In Figure 2.1 we can see a scheme of the experimental setup. We are interested in the conditioning procedures and their breakdown voltage. The experiments are conducted until the average voltage breakdown remains constant. The paper presents four different tests with varying anode and cathode configurations, the exact configurations can be seen in Figure 2.3. Those different test configurations are the basis of our dataset and we refere to the different configurations for the remaining part of the report with tc1,..., tc4. The authors of the original paper also developed a probabilistic tool to predict the breakdown voltage of a configuration. In Figure 2.2 we can see the comparison between the experiments and the probability density prediction of the developed tool. For tc1 and tc4 the prediction fits well but the tool seems to struggle with tc2 and tc3. This is the reason why we decided to analyze tc2 and tc3 for potential anomalies.

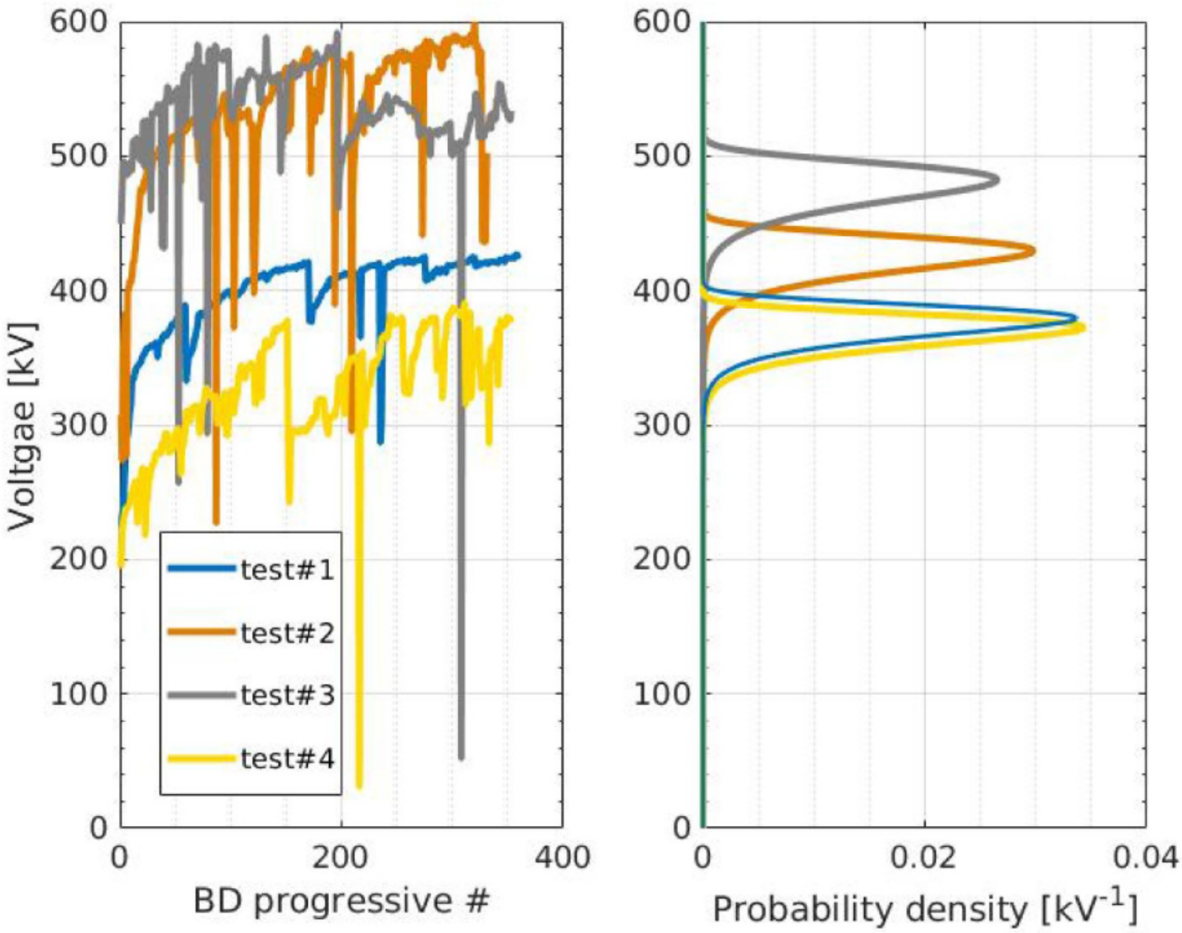

Figure 2.2: A comparison between the results of the experiments for the test configurations and the probability density prediction (taken from page 12 of the original paper[1]).

2.2 Comparison of the Datasets

During the experiments different signals are recorded, the ones we used in our analysis are:

- IM_MIS: Measured Negative Current
- IP_MIS: Measured Positive Current
- ITR_MIS: Measured Pressure

- SCINT_MIS: Scentilator (XRAY)
- ANALOG_IN (total voltage):
  = VP_MIS + |VM_MIS|.

Test #	Cathode	Anode	Gap length (mm)
T#1	Sphere ϕ40 mm	Plane ϕ108 mm	33
T#2	Sphere ϕ40 mm	Plane ϕ108 mm	72
T#3	Sphere ϕ40 mm	Plane ϕ108 mm	147
T#4	Sphere ϕ24 mm	Sphere ϕ24 mm	30

Figure 2.3: The different configurations used in the test cases (taken from page 5 of the original paper[1]).

We obtained the data of the experiments from the authors of the original paper. However, due to miscommunication on our side, some files for tc1(11/12) and tc2(16/21) are missing. In Figures 2.4 and 2.5 we can see a comparison of the data we used in your analysis and the one from the original paper respectively. Aside from the missing files dissimilaritieses are due to different methods of determining the breakdown timings.

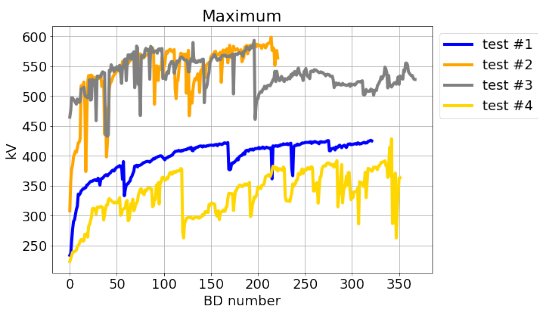

Figure 2.4: Data we used

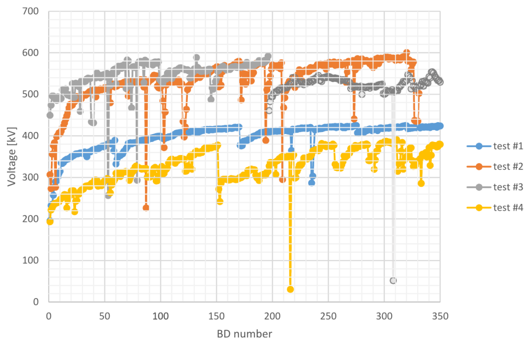

Figure 2.5: Original paper, p. 9 [1].

3 Preprocessing and Feature Extraction

3.1 Preprocessing

In order to find anomalies in tc2 and tc3 our first task was to cut the individual conditioning processes into ramp-ups. We defined a ramp-up from minimum to maximum (break down) in the ANALOG_IN signal. Figure 3.1 shows the ANALOG_IN signal of tc1 as an example. The blue crosses are the minima and the red crosses are the maxima. We determined the minima and maxima with *scipy.signal.find_peaks* and afterwards improved the obtained results for all test cases by hand.
Since our dataset does not only contain the ANALOG_IN channel but also IM_MIS, IP_MIS and ITR_MIS we simultaneously cut those channels at the exact same points in time. Figure 3.2 shows an exemplary ramp-up with all five channels.

After the cutting process, we were able to do a first comparison of the four different test cases. Figure 3.3 shows the length of the ramp-ups for every test case and the corresponding histogram. Most notably tc2/tc3 seem to have longer ramp-ups especially at the beginning of the conditioning process.

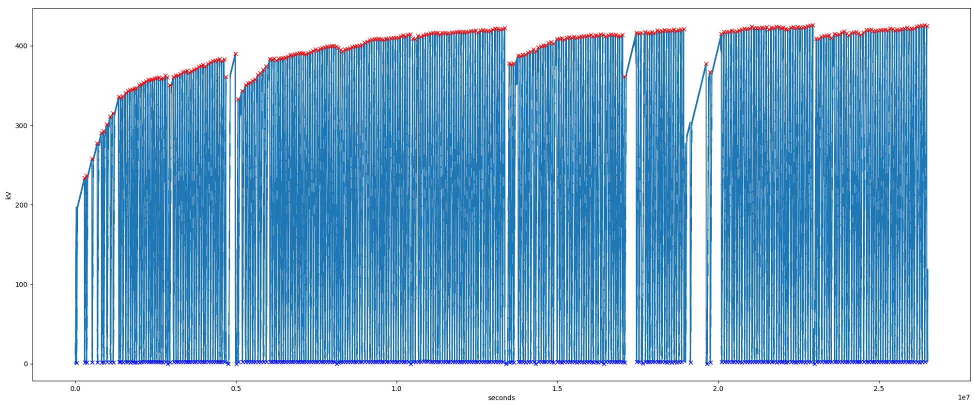

Figure 3.1: Tc1 devided into individual ramp-ups.

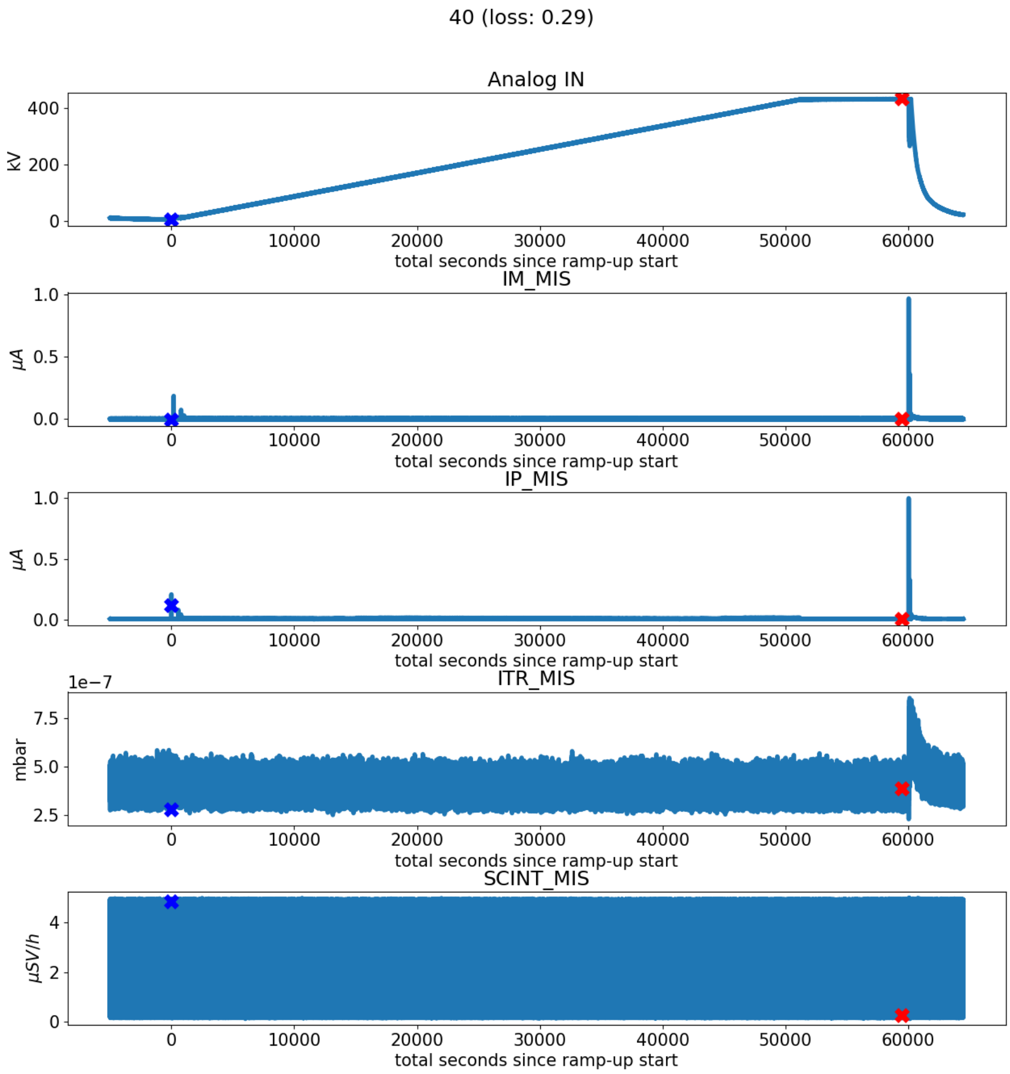

Figure 3.2: Exemplary ramp-up with all five channels.

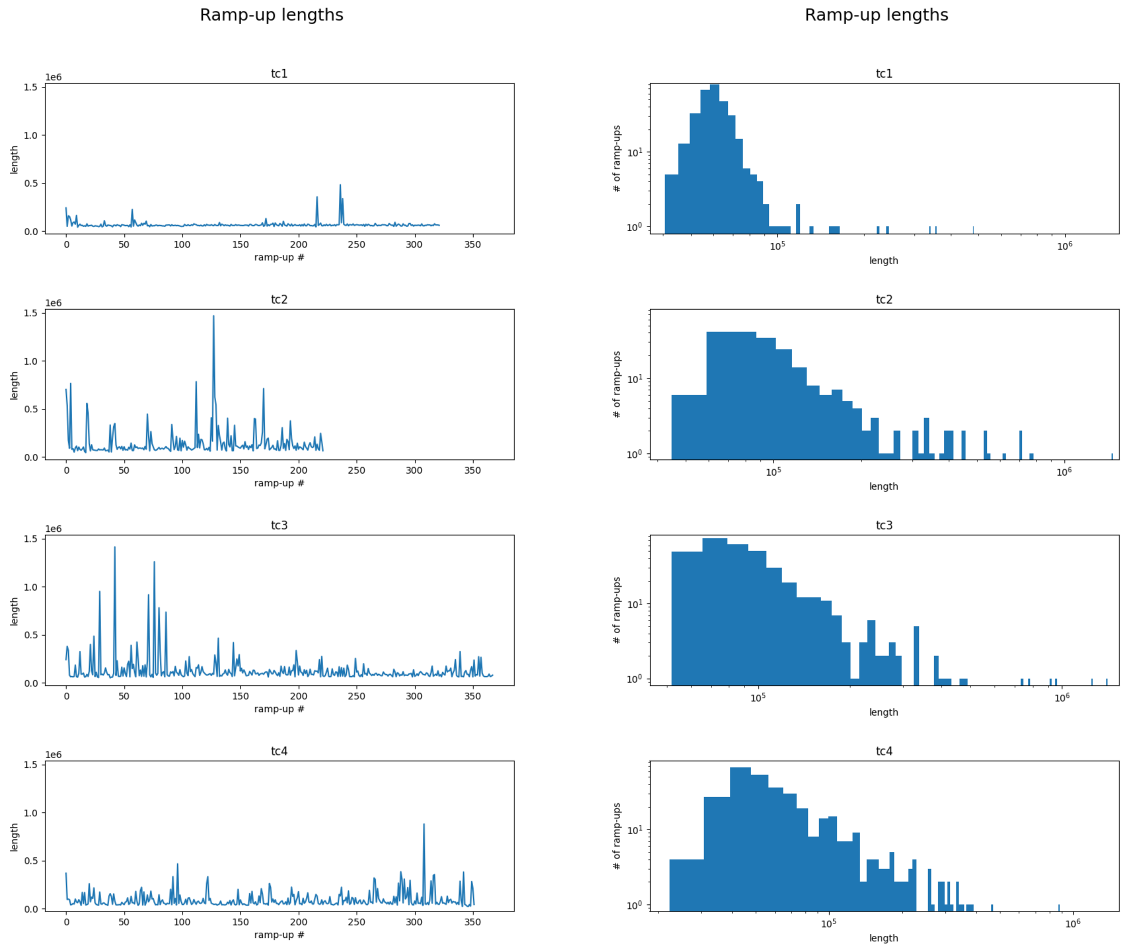

Figure 3.3: Ramp-up length for all four test cases in comparison.

3.2 Feature Extraction

For each individual ramp-up and every channel, we extracted a number of features using tsfresh [3]. TSfresh does the feature extraction completely automatic once one has specified the desired features. We extracted in total 37 features like minimum, maximum, mean and more advanced features like Fourier coefficients. The feature selection was taken from a kaggle notebook [4] and every used feature with its configuration can be found in the code.

3.3 Anomaly detection via LSTM autoencoder

We then use the extracted features as input for our LSTM model. Therefore the dimensions of our dataset are: conditioningPhases $\times$ ramp-ups $\times$ signals $\times$ features.
Our model has the same architecture as detailed in the blog post by Larzalere [5]. We used tc1 and tc4 as training set for the LSTM model. We trained the network for 100 epochs and used a batch size of 10. As an optimizer we used Adam.
After the training, we ranked ramp-ups from tc2 and tc3 according to their reconstruction loss. We further analyzed the five ramp-ups with the highest reconstruction loss for tc2 and tc3.

4

Analysis of potential anomalies in test case 2

In this section we will take a closer look at the five ramp-ups with the highest reconstruction loss for tc2 and tc3. First we will look at the PCA of the input features to spot similarities in anomalies and then we will inspect the histograms of the features with the highest contribution to the reconstruction loss. Last but not least we will inspect the actual ramp-ups.

Figure 4.1 shows the result of the PCA to two dimensions. The individual ramp-ups are colored based on their reconstruction loss and the ramp-ups with the highest reconstruction loss are numbered. This shows us that the anomalies detected by the LSTM autoencoder are also outliers in regard to the input features and that four of the top five potential anomalies share common traits (11, 59, 61, 159).
Figure 4.2 allows us to determine when in the conditioning process the anomalies appear.

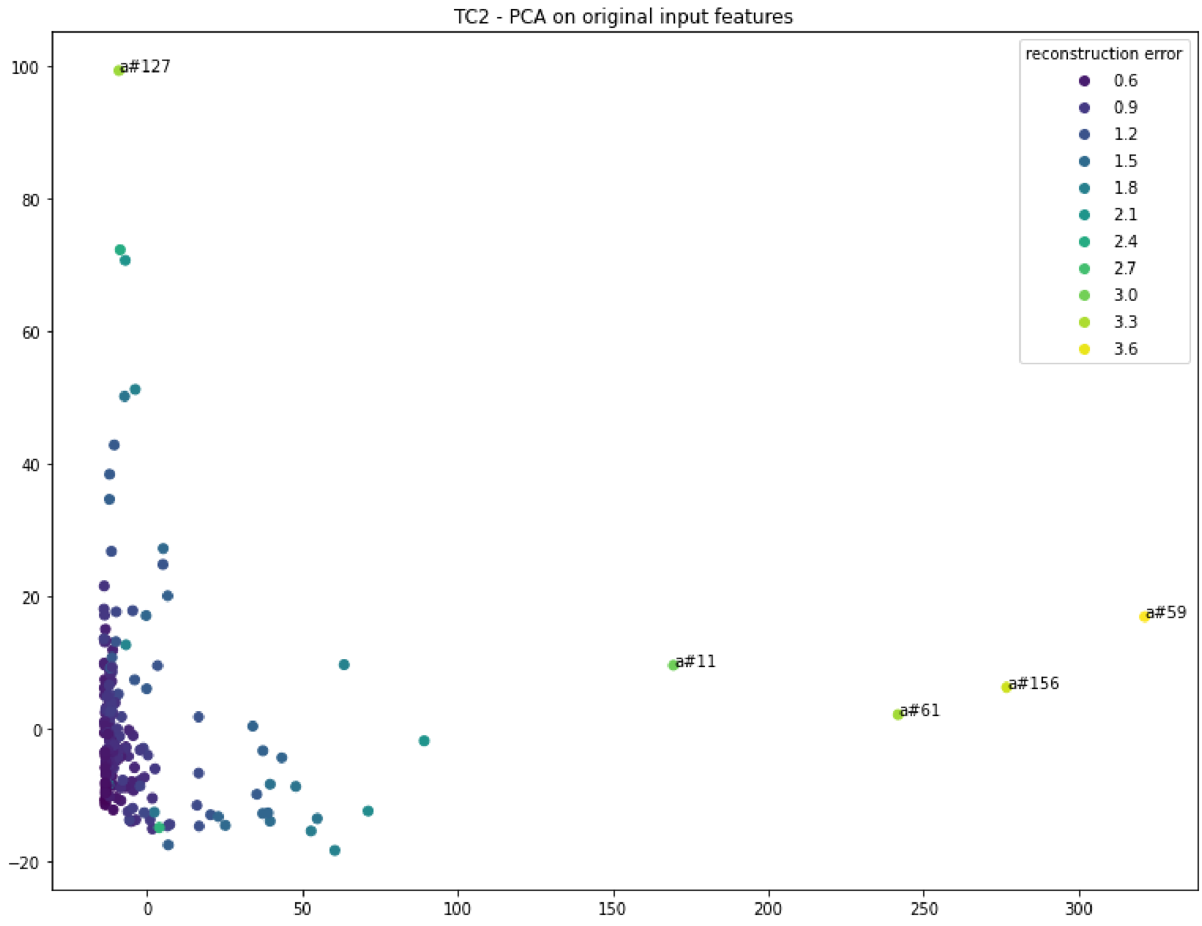

Figure 4.1: Each point is a ramp-up. The points are colored based on their reconstruction loss.

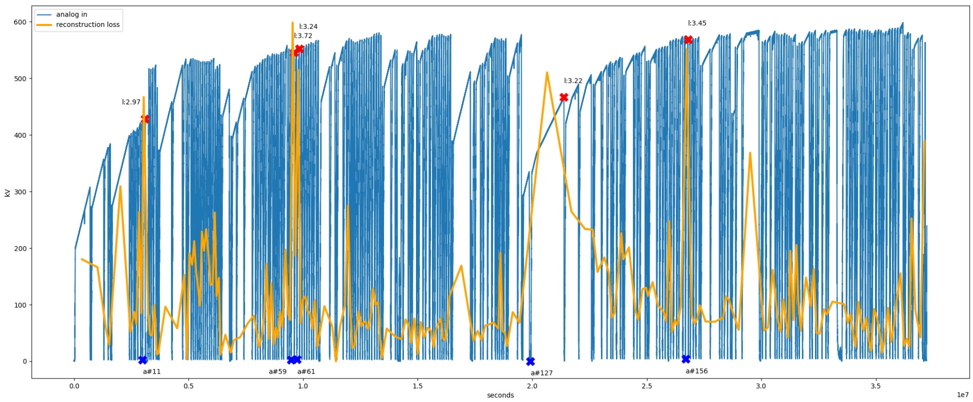

Figure 4.2: The ANALOG_IN signal with the anomalies and the reconstruction loss.

4.1 TC2-anomaly cluster 11, 59, 61, 156

As anomalies 11, 59, 61 and 156 share common traits we will focus on anomalies 59 and 156 since they have the highest reconstruction loss in the cluster.
The features that contributed most to the reconstruction loss are *IP_MIS_c3_lag_mean* (statistic to measure non-linearity in ramp-up), *IP_MIS_value_variance* (variance of the ramp-up) and *IP_MIS_fft_coeff_imag_mean* (imaginary part of the Fourier coefficients of the one-dimensional discrete Fourier Transform). Note that all three features are from the IP_MIS signal. Figure 4.6 shows that tc2 and tc3 obtain higher values for every feature more often. Since the three features have a high correlation as shown by the correlation matrix in Figure 4.3 we will concentrate on the variance since it is the most intuitive. Figure 4.7 we can see the actual ramp-ups in comparison to ramp-ups with low reconstruction loss. The higher variance in the IP_MIS signal can be easily seen.

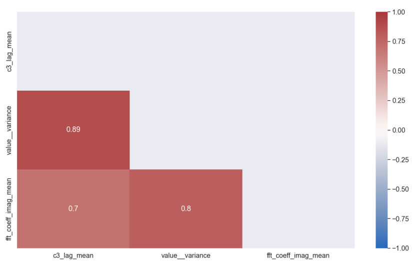

Figure 4.3: 11, 59, 61, 156

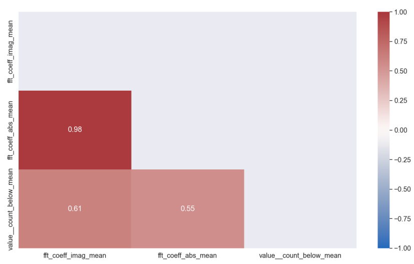

Figure 4.4: 127

Correlation matricis of the features that contributed most to the reconstruction loss.

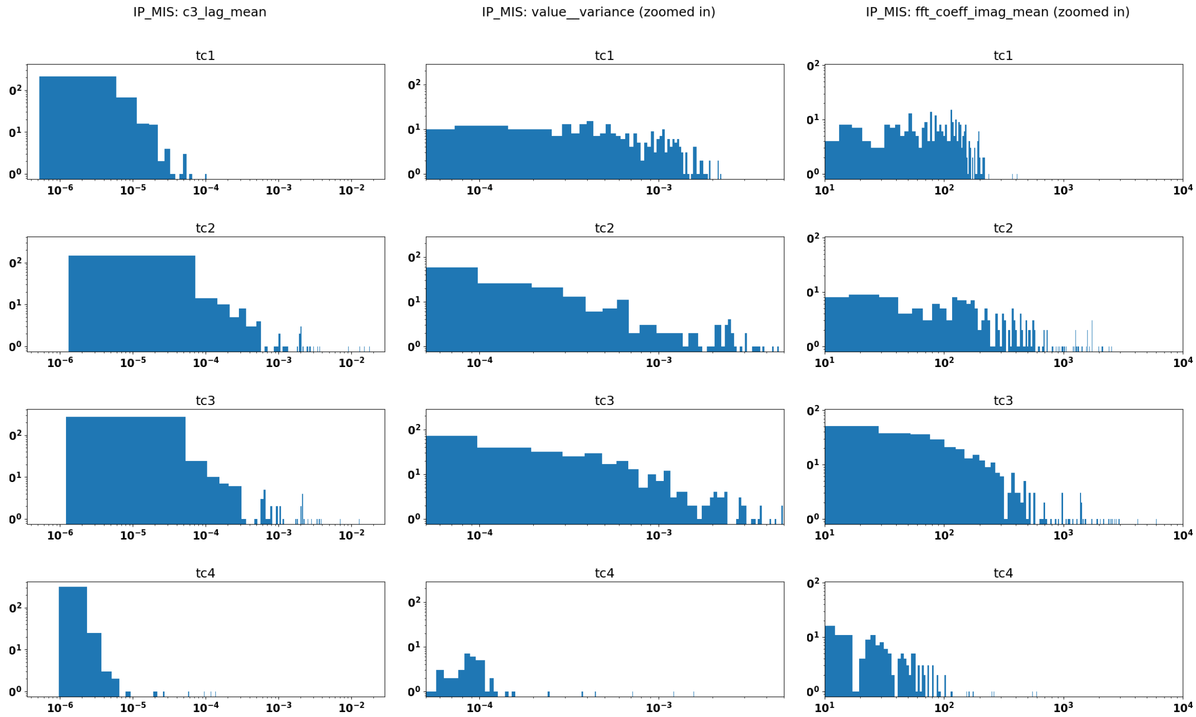

Figure 4.6: Histograms of the features that contributed most to the reconstruction loss.

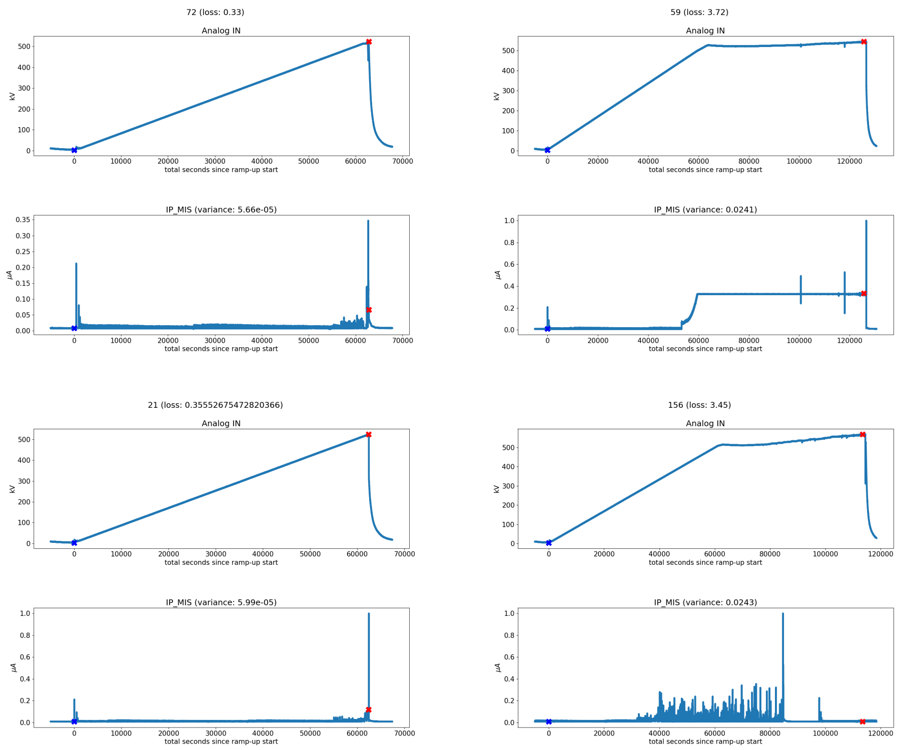

Figure 4.7: Comparison between conventional ramp-ups (left) and the anomalies (right).

4.2 TC2-anomaly ramp-up 127

he features important for ramp-up 127 are *IM_MIS fft_coeff_imag_mean* (imaginary part of the Fourier coefficients of the one-dimensional discrete Fourier Transform), *ANALOG_IN value___count_below_mean* and *IM_MIS fft_coeff_abs_mean* (absolute value of the Fourier coefficients).
The correlation matrix of those features is shown in Figure 4.4. The histograms in Figure 4.10 are quite similar to the ones inspected before: once again there are more outliers for tc2/tc3 in all three histograms. In Figure 4.8 we can see why ramp-up 127 is an anomaly in the value count below mean of ANALOG_IN and the differences in the IM_MIS signal when compared to more conventional ramp-ups.

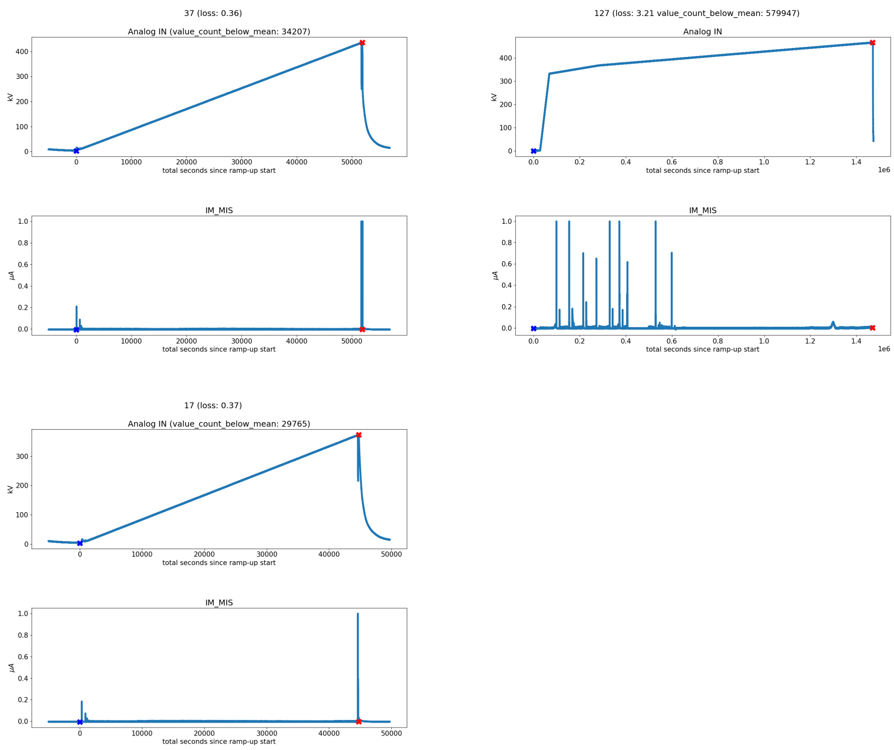

Figure 4.8: Comparison between conventional ramp-ups (left) and the anomalies (right).

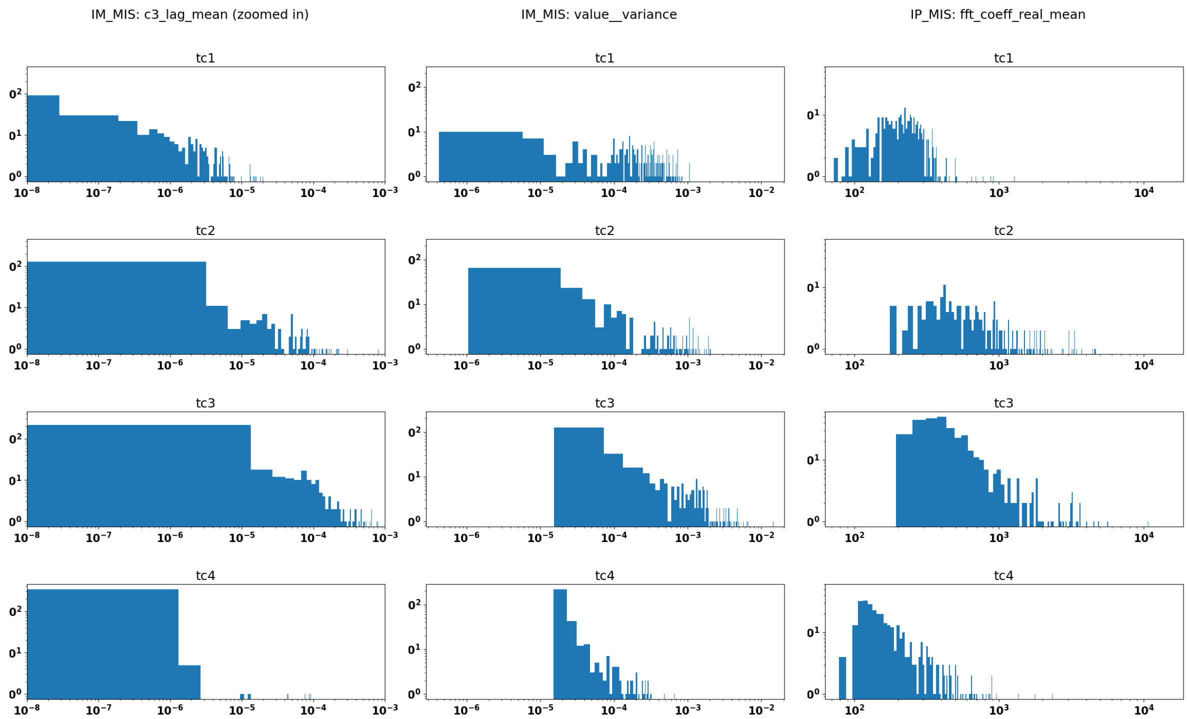

Figure 4.9: Histograms of the features that contributed most to the reconstruction loss.

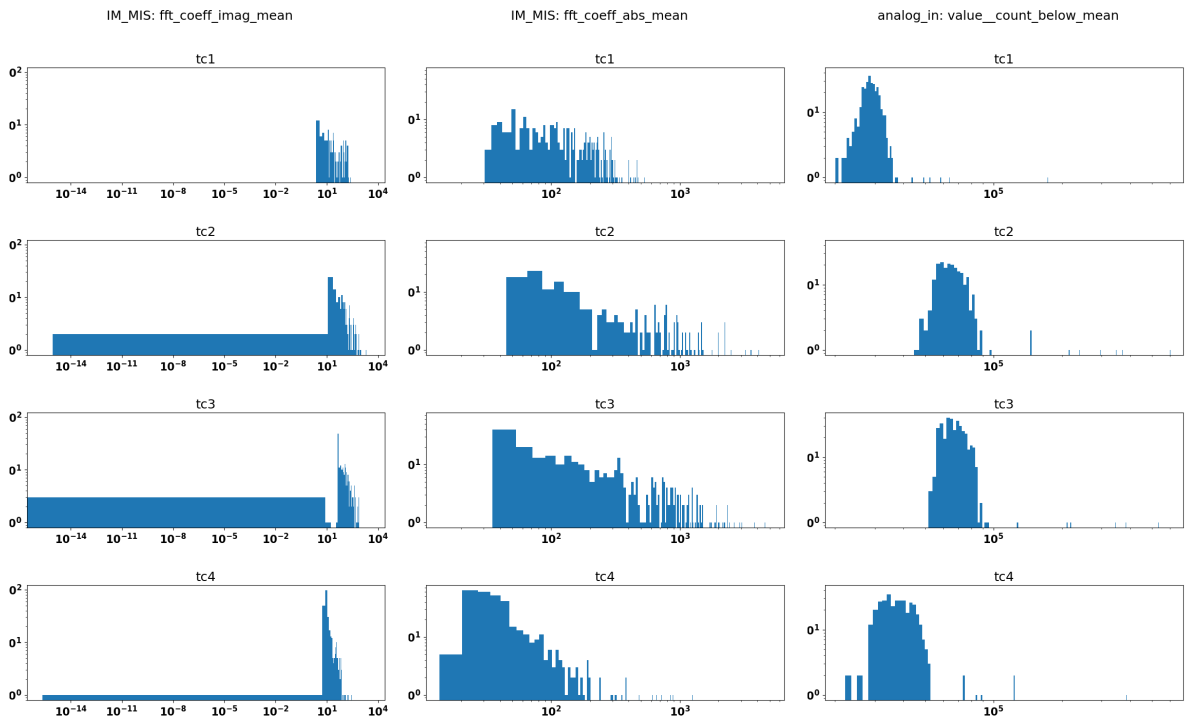

Figure 4.10: Histograms of the features that contributed most to the reconstruction loss.

4.3 Analysis of potential anomalies in test case 3

In this section, we will concentrate on the five ramp-ups with the highest reconstruction loss of tc3. The results are mostly in line with the ones discussed above for tc2. Therefore we will provide shorter explanations.
We once again start off with the PCA and reconstruction loss plot in Figures 4.11 and 4.12. We can divide the found anomalies into two distinct anomalies, 72 and 42 and a cluster of anomalies 26, 217 and 261.

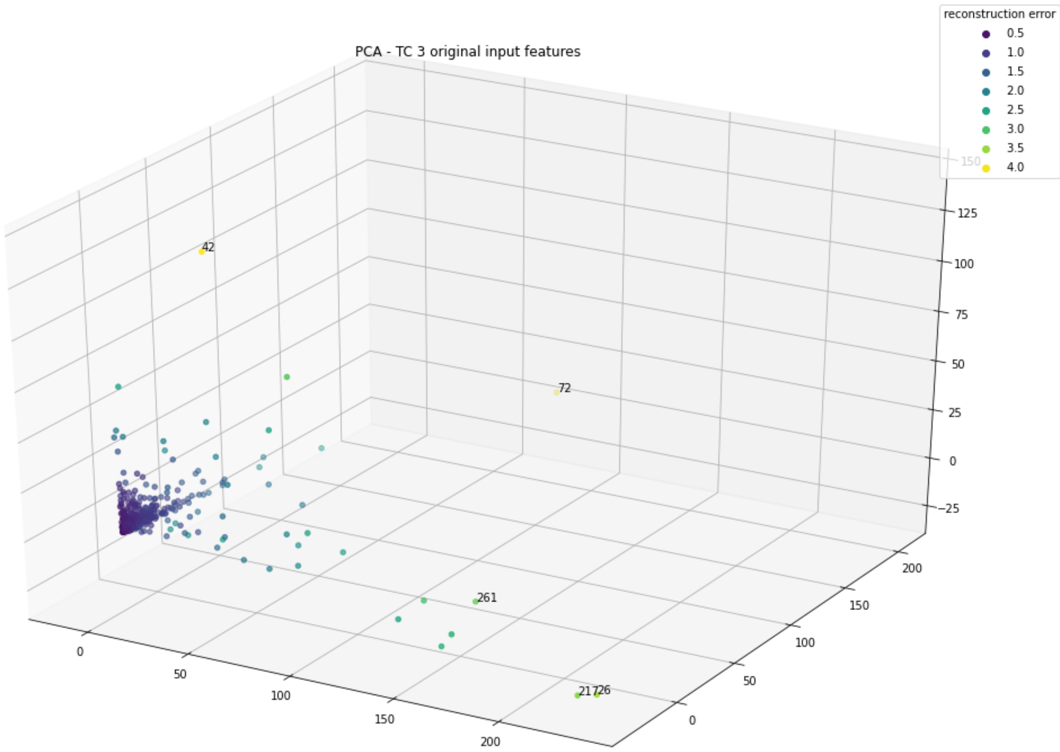

Figure 4.11: Each point is a ramp-up. The points are colored based on their reconstruction loss.

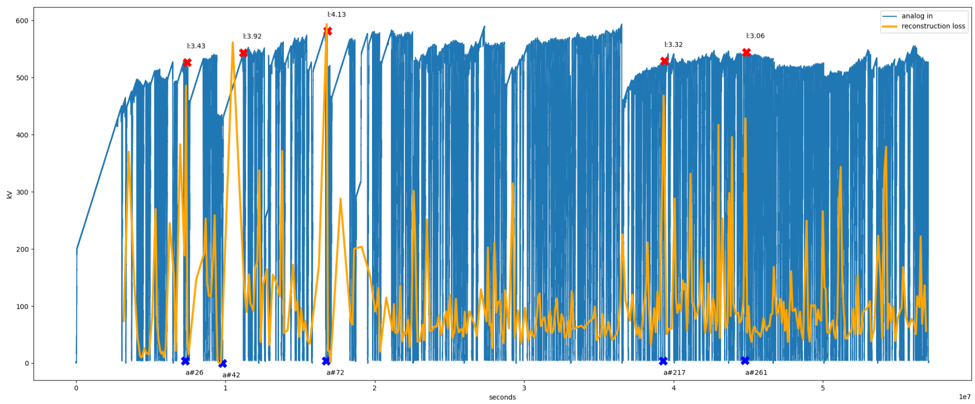

Figure 4.12: The ANALOG_IN signal with the anomalies and the reconstruction loss.

4.3.1 TC3-anomaly ramp-up 72

The three features that contributed most to the reconstruction loss are *IM_MIS_c3_lag_mean*, *IM_MIS_value__variance* and *IP_MIS_c3_lag_mean*. Figure 4.13 displays the correlation matrix of those features. If we look at the corresponding histograms in Figures 4.9 and 4.10 we see once again that tc2/tc3 obtain higher values for all three metrics when compared to tc1/tc4. Figure 4.17 shows the actual ramp-up in comparison to more conventional ramp-ups. The higher variance is present in all shown signals.

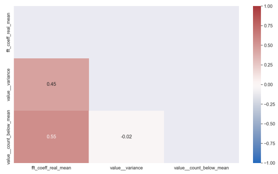

Figure 4.13: 72

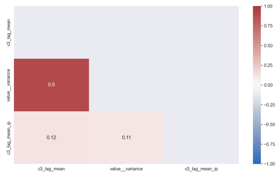

Figure 4.14: 42

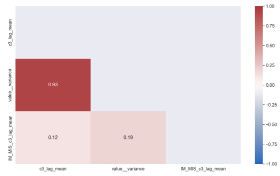

Figure 4.15: 26, 217, 261

Correlation matricis of the features that contributed most to the reconstruction loss.

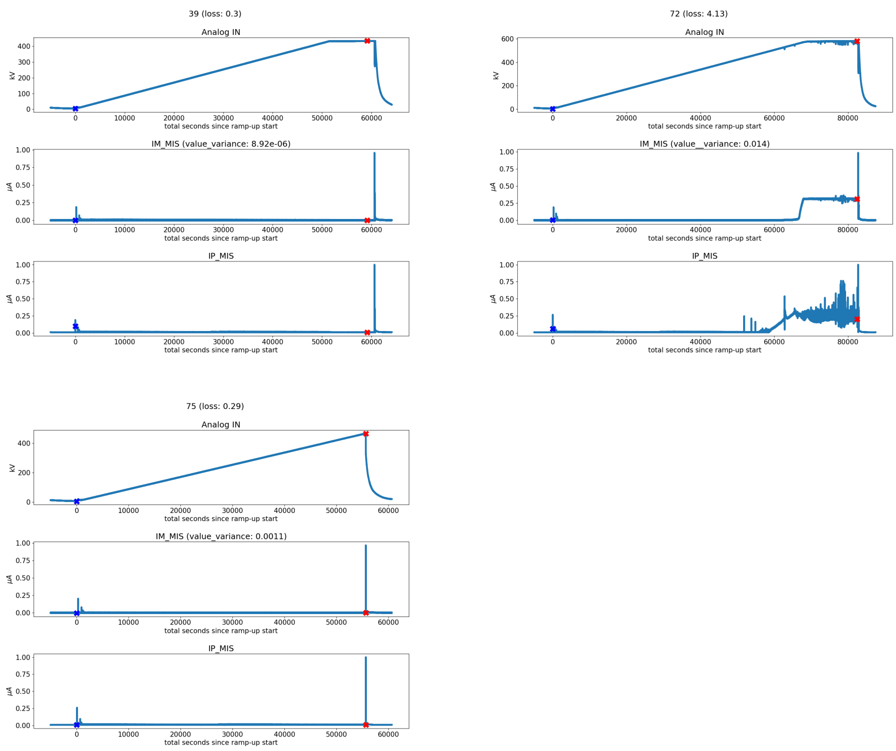

Figure 4.17: Comparison between conventional ramp-ups (left) and the anomalies (right).

4.3.2 TC3-anomaly ramp-up 42

The three features that we want to highlight are: *IP_MIS_fft_coeff_real_mean*, *IP MIS_value_variance* and *ANALOG_IN_value__count_below_mean* (see histograms Figure 4.9 and 4.10 and correlation matrix at Figure 4.14).
In Figure 4.18 we can see the the actual ramp-up with the two signals of the selected features.

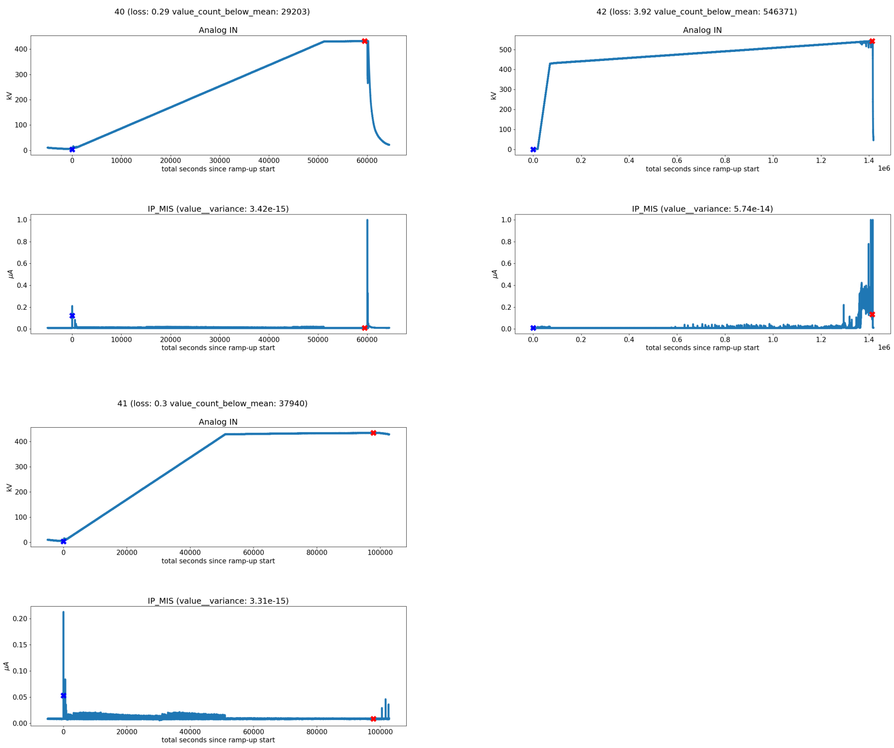

Figure 4.18: Comparison between conventional ramp-ups (left) and the anomalies (right).

4.3.3 TC3-anomaly cluster 26, 217, 261 - LSTM

For this cluster the most important features are: *IP_MIS_c3_lag_mean*, *IP_MIS_value___variance* and *IM_MIS_c3_lag_mean* (see histograms Figure 4.10 and 4.9 and correlation matrix at Figure 4.15). We picked the two anomalies with the highest reconstruction loss of this cluster (26 and 217) and compared them to more conventional ramp-ups in Figure 4.19.

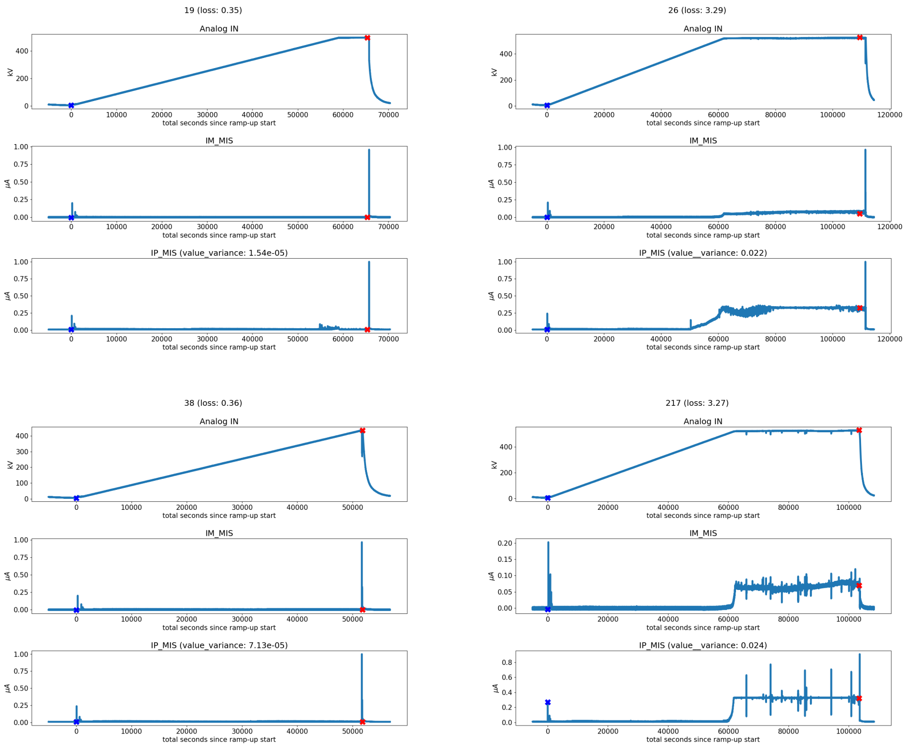

Figure 4.19: Comparison between conventional ramp-ups (left) and the anomalies (right).

5 Conclusion

Most of the anomalies we analyzed were found in the IP_MIS or IM_MIS signal. Therefore the main difference between tc1/tc4 and tc2/tc3 seems to be a bigger variance within those signals. Another interesting finding is that tc2 and tc3 have longer ramp-ups in the beginning. We conclude that increased current variance and longer ramp-ups in the initial phase of the conditioning seem to be the main indicators for higher voltage compared to the prediction of the probabilistic model.
Additionally, the distributions of the analyzed features for tc2/tc3 were often quite similar. This indicates that an improvement of the breakdown prediction model for one test case might carry over to the other.

Motivated by our findings regarding the variance we plotted the variance per ramp-up against the max kv in Figure 5.1. The Figure shows that variance and maximum kv per ramp-up seem to be correlated.

To further improve the approach of finding the anomalies one might try to cluster the anomalies in their latent space representation and consult the physicists on which clusters are explainable an which need further inspection.

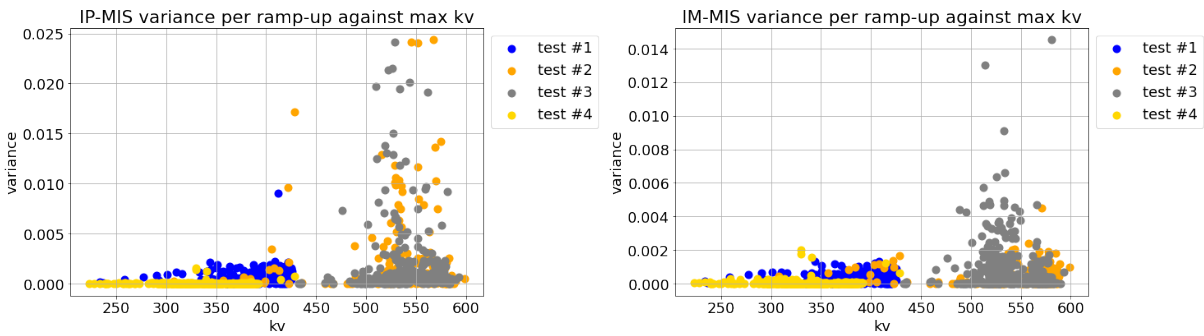

Figure 5.1: For both signals the variance increases as the voltage rises.

Bibliography

[1] N. Pilan, S. Deambrosis, A. D. Lorenzi, M. Fincato, C. Fontana, R. Gobbo, L. Lotto, E. Martines, O. M. Cormack, R. Pasqualotto, T. Patton, G. Pesavento, F. Pino, E. Spada, S. Spagnolo, and M. Zuin, "Study of high DC voltage breakdown between stainless steel electrodes separated by long vacuum gaps," *Nuclear Fusion*, vol. 60, no. 7, p. 076 010, Jun. 2020. DOI: 10.1088/1741-4326/ab8d03. [Online]. Available: https://doi.org/10.1088/1741-4326/ab8d03.

[2] [Online]. Available: https://github.com/cobermai/rfx_discharge_prediction/tree/anomaly_detection.

[3] [Online]. Available: https://tsfresh.com/.

[4] [Online]. Available: https://www.kaggle.com/superluminal098/tsfresh-features-and-regression-blend.

[5] [Online]. Available: https://towardsdatascience.com/lstm-autoencoder-for-anomaly-detection-e1f4f2ee7ccf.

List of Figures

2.1 Experimental Setup scheme taken from page 4 of the original paper[1]. 4
2.2 A comparison between the results of the experiments for the test configurations and the probability density prediction (taken from page 12 of the original paper[1]). 5
2.3 The different configurations used in the test cases (taken from page 5 of the original paper[1]). 6
2.4 Data we used 6
2.5 Original paper, p. 9 [1]. 6

3.1 Tc1 devided into individual ramp-ups. 7
3.2 Exemplary ramp-up with all five channels. 8
3.3 Ramp-up length for all four test cases in comparison. 9

4.1 Each point is a ramp-up. The points are colored based on their reconstruction loss. 11
4.2 The ANALOG_IN signal with the anomalies and the reconstruction loss. 12
4.3 11, 59, 61, 156 12
4.4 127 12
4.5 Correlation matricis of the features that contributed most to the reconstruction loss. 12
4.6 Histograms of the features that contributed most to the reconstruction loss. . . 13
4.7 Comparison between conventional ramp-ups (left) and the anomalies (right). . . 13
4.8 Comparison between conventional ramp-ups (left) and the anomalies (right). . . 14
4.9 Histograms of the features that contributed most to the reconstruction loss. . . 15
4.10 Histograms of the features that contributed most to the reconstruction loss. . . 15
4.11 Each point is a ramp-up. The points are colored based on their reconstruction loss. 16
4.12 The ANALOG_IN signal with the anomalies and the reconstruction loss. 16
4.13 72 17
4.14 42 17
4.15 26, 217, 261 17
4.16 Correlation matricis of the features that contributed most to the reconstruction loss. 17
4.17 Comparison between conventional ramp-ups (left) and the anomalies (right). . . 17
4.18 Comparison between conventional ramp-ups (left) and the anomalies (right). . . 18
4.19 Comparison between conventional ramp-ups (left) and the anomalies (right). . . 19

5.1 For both signals the variance increases as the voltage rises. 20