Impact of the Temporal Distribution of Faults on Prediction of Voltage Anomalies in the Power Grid

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***Abstract*—Power Quality (PQ) data from 49 nodes in the Norwegian power grid was analyzed for three types of voltage anomalies; line interruptions, voltage dips and ground faults. It was observed that the probability that a new anomaly has occurred as a function of time passed since the previous anomaly approximately follows a logarithmic curve. Thus the hazard rate of a new anomaly declines significantly as the time since the previous anomaly increases. A machine learning model was developed to try to predict voltage anomalies 10 minutes in advance based on the presence of early warning signs in the preceding 50 minutes.**

***Index Terms*—Power quality analysis, power systems, machine learning, fault prediction**

I. Introduction

In Norway in 2018, roughly 15.1 GWh of energy was not supplied to end users due to unplanned power interruptions. Although this number may seem relatively low compared to the 120 000 GWh that were successfully delivered, it is estimated that power outages, together with other power quality anomalies such as ground faults and voltage dips, cost Norwegian end users tens of millions of Euro annually [1].

Mahela et. al. [2] provides a review of more than 150 research publications published between 1986 and 2014 that tackle the subject of detection and classification of power quality anomalies. It found that the most common detection/feature extraction techniques were the wavelet-, S-, Fourier- and Hilbert-Huang transforms, while the most commonly used classification methods were artificial neural networks, support vector machines, genetic algorithms, fuzzy expert systems and evolutionary algorithms. Another similar review was done by Misha in 2019 [3].

However, fault detection is a fundamentally reactive process where the model tries to detect and classify a fault after it has already started. It would be more useful to have a proactive model that is able to predict faults in advance. E.g. to have a model that is able to predict with high confidence that a new fault is about to occur in ca. 10 minutes on a given node, so that system operators can get a 10 minute head start on the problem.

Real-time monitoring of power systems has experienced impressive development in the last 10-15 years. Grid companies globally have increasingly installed devices such as Power Quality Analysers (PQA), Phasor Measurement Units (PMU) and Advanced Metering Infrastructure (AMI) to increase their situational awareness [4]. The increasing number of monitoring instruments installed in the grid has given companies more information about the present grid condition, which has made grid operation more efficient.

In the period before a fault occurs there may be certain early warning signs in the voltage data indicating that something is amiss. A machine learning model trained on the large amount of historical data available may be able to learn to recognize these signs. The long-term objective of this research is to have machine learning models running live on nodes in the electric grid, that give a warning to system operators when the model predicts that there is an elevated likelihood that a fault is about to occur within the next time frame.

Fault prediction is a more difficult problem than fault detection. The extent to which voltage anomalies can be reliably predicted a long time in advance purely based on PQA measurements is currently an unsolved research question. Previous research literature on fault prediction using PQA data is scarce. The most relevant articles are ones that look at related, but somewhat different, problems like prediction of power quality using weather measurements [5], predictions done on lower voltage networks [6] or predictions with shorter forecasting horizons, that are in the span of seconds instead of minutes [7].

The main objective of this paper is to emphasize how important it is to take the temporal distribution of faults into account when trying to predict future voltage anomalies.

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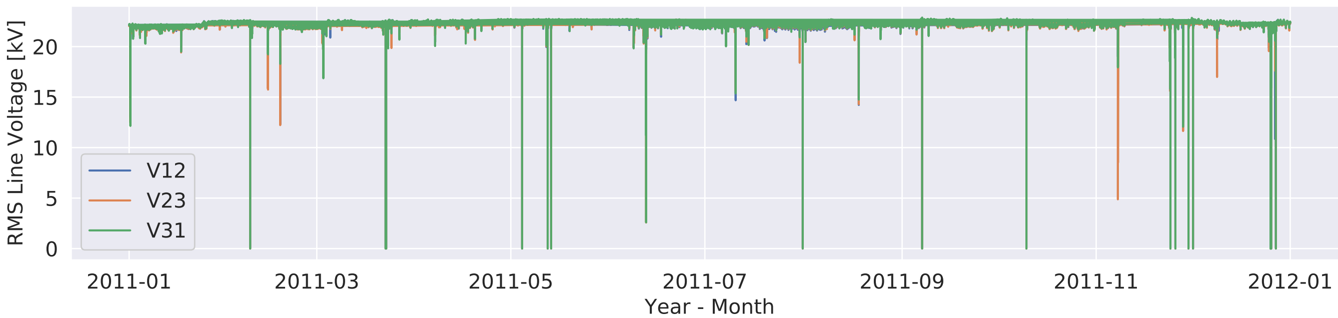

Fig. 1. PQA data from a node spanning a one-year time period. A number of voltage dips and line interruptions can be seen. V12 is the RMS phase-to-phase voltage, a.k.a the line voltage, between line 1 and 2. V23 and V31 are defined similarly.

Section II will introduce the data set that was used and discuss how the faults in the data set exhibit strong clustering behavior in time, section III will describe the prediction model that was used, section IV contains the results from testing the prediction model, while section V will discuss challenges with the methodology and potential future work.

II. Fault distribution

This study uses PQA data [8] collected from a total of 49 nodes in the Norwegian power grid, belonging to 9 different distribution system operators (DSOs) and the Norwegian transmission system operator (TSO). The data consisted of waveform and RMS line voltage, phase voltage and phase current measurements sampled continuously at very high measuring frequencies, generally at 50 kHz. The data spans the period from January 2009 to early March 2020. The nominal line voltages at the measurement points in the grid varied from 10 to 420 kV. A total of roughly 270 years of PQA data was analysed. Thus, there was on average ca. 5-6 years of historical data from each node, although the number of years of available data varied significantly from node to node. The node with the least amount of data contained only 4 months of measurements, whereas the nodes with the most data contained measurements spanning a period of 10 years. Figure 1 shows one year of RMS line voltage data from one of the nodes.

AHA [9], an event analysis software program, was used on the data to generate lists of fault events. The fault events were divided into three categories. The first category was line interruptions, defined as a time period lasting more than one half-cycle where all three RMS line voltages dropped below 5 % of the nominal line voltage. The second category was voltage dips, defined as a time period where one or several of the three RMS line voltages dropped below 90 % of the nominal line voltage without all three dropping below 5 %. The third category was ground faults, which match one or both of the following two criteria: a) time periods where one of the three RMS phase voltages went above 130 % of the nominal phase voltage while the other two phase voltages were below the nominal phase voltage and b) the opposite scenario where one of the three phase voltages went below 70 % of the nominal phase voltage, while the other two stayed above 100 %.

Note that minor voltage dips frequently do not cause any significant adverse effects in the power grid. Thus referring to these anomalies as faults may be somewhat misleading. However, for the sake of simplicity, in this paper the terms anomaly and fault are used interchangeably and refers exclusively to any event that belongs to one of the three categories described above.

A total of 69 612 discrete fault events were detected in the overall data set. Of these, 47 612 were ground faults, 19 813 were voltage dips and the remaining 2187 were line interruptions. The mean frequency of faults averaged over all nodes was one fault every nine days, although the fault frequency varied significantly from node to node. The node with the highest fault frequency experienced on average one fault every 7-8 hours, whereas the node with the lowest fault frequency only experienced one fault every 65 days. The proportion of different types of faults also varied significantly from node to node. The node in Figure 1, for instance, had an unusually large number of line interruptions, but also had an unusually small number of voltage dips.

Figure 2 shows data from the hour preceding a random ground fault and the hour preceding a random voltage dip. The hour of data that precedes the voltage dip looks completely inconspicuous. For the ground fault, on the other hand, there is a fairly clear-cut event starting around 23 minutes before the fault occurs. Faults that are preceded by early warnings signs in the PQA data, like the ground fault in the figure, are ones that motivate the idea that some faults may be reliably predicted in advance using machine learning models. Unfortunately, for a large number of faults, like the voltage dip in the figure, there are no visible signs in the PQA data at all that a fault is about to occur.

66.3 % of the detected faults started less than one second after the end of the previous fault on the same node. The reason that this percentage is so high can be explained by looking at Figure 3, which shows an example of what appears to be a series of two or three ground faults. However, because the third RMS phase voltage constantly switches between being over and below 130 % of the nominal phase voltage, each brief

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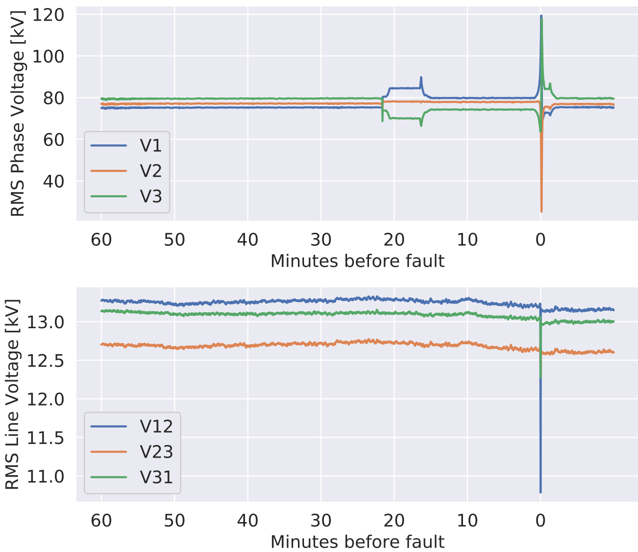

Fig. 2. Top plot shows an example of a ground fault that has a noticeable event starting at around 23 minutes before the fault. Bottom plot shows an example of a voltage dip with no disturbances in the preceding hour.

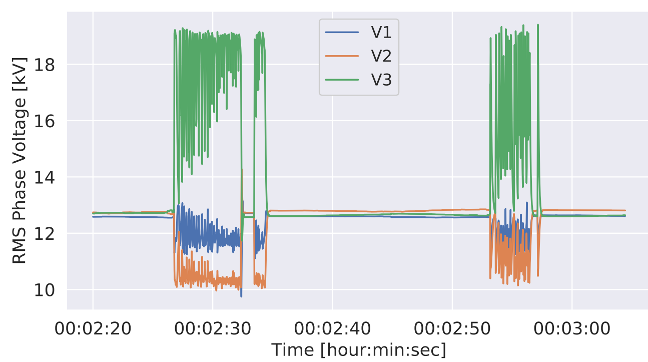

Fig. 3. Example showing intermittent ground faults.

period where it is above the threshold for being considered a ground fault was counted by the event analysis program as a separate fault. Thus the fault on the left was actually registered as a sequence of 19 short ground faults, while the one on the right was registered as 20 separate faults.

Even by merging faults of the same type that occur less than one second after each other and categorizing them as the same event, it is still ambiguous what exactly constitutes a discrete fault event. E.g. the fault on the left in the plot is clearly split in two, with roughly a one-second period in-between where the voltages behave normally. It is debatable whether these should be categorized as one or two fault events. Furthermore, the previous fault before the time period shown in the plot occurred more than an hour earlier and the next fault occurred more than two hours later. Thus, the 17 second gap between these two ground faults is fairly small in comparison and an argument could be made that they should be considered part of the same fault event.

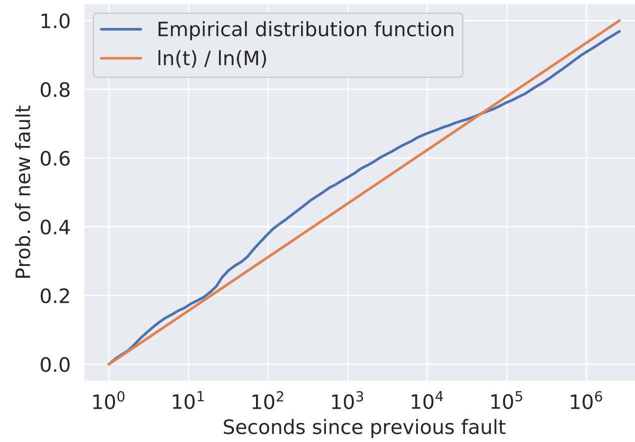

Fig. 4. Probability of a new fault having occurred as a function of time since previous fault. Note the logarithmic scale on the x-axis.

Time passed	**Prob(new fault)**
1 second	0
10 seconds	0.18
1 minute	0.33
10 minutes	0.52
1 hour	0.62
1 day	0.76
1 week	0.87
1 month	0.97

TABLE I
PROBABILITY THAT A NEW FAULT HAS OCCURRED AS A FUNCTION OF TIME PASSED SINCE PREVIOUS FAULT.

Figure 4 shows the probability that a new fault will have occurred within t seconds after the previous fault, with the x-axis plotted on a logarithmic scale. In other words it shows the empirical distribution function for the duration between subsequent faults. For the sake of this plot, fault events that occurred less than one second after each other were merged together and considered to be the same event. Table I shows some specific values from the plot.

The result seen in the figure is very interesting. The empirical distribution follows a curve that resembles a straight line when plotted on a logarithmic scale. This means that it can be approximated by the function

$$F(t|t > 1) \approx \frac{ln(t)}{ln(M)}. \quad (1)$$

M is the constant $30 \cdot 24 \cdot 60 \cdot 60$, corresponding to the number of seconds in a month. Thus the hazard function, the probability that a new fault will occur within a short time period from the present, e.g. within the next minute, declines sharply as the time since the previous fault increases.

Since some nodes suffer from more faults than others, and the faults on some nodes appear to display more clustering than the ones on others, the relationship in Figure 4 does not hold on all nodes if you break the figure down on a node-by-node basis. However, a logarithmic cumulative probability

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function appeared to be a reasonably good approximation on the majority of nodes.

Figure 5 shows the cumulative fault duration distribution. As can be seen from the plot, the duration of most faults is relatively short; ~ 90 % of all faults last less than a second and ~ 99 % last less than 10 seconds. Most of the faults that lasted more than 10 seconds were line interruptions. Although, as can be seen in the figure, if fault events that happen in close succession are merged, the average length of faults will increase.

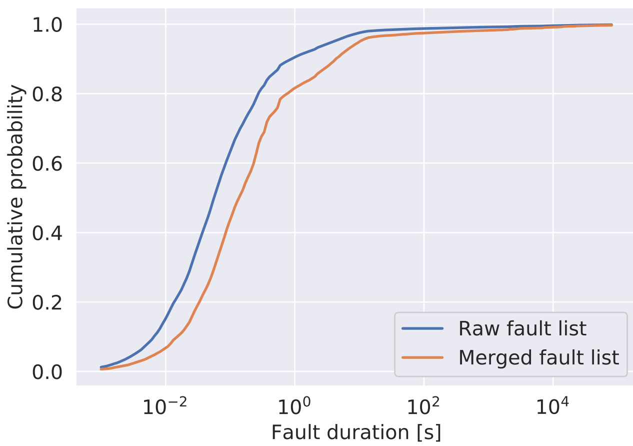

Fig. 5. Empirical cumulative distribution for fault duration. The blue line is for the non-merged fault list, while the orange line shows how the distribution changes when faults of the same type that occur within 1 second of each other are merged together.

Figures 4 and 5 do not change much if only ground faults or voltage dips are studied separately, although ground faults appeared to cluster together slightly more than voltage dips. However, line interruptions were clustered together significantly less than the other two fault types and typically lasted significantly longer. Of line interruptions, ~ 40 % lasted longer than 10 seconds, ~ 15 % lasted longer than an hour and ~ 3 % lasted longer than a day.

Figure 6 displays a histogram of the extreme values of voltage dips and line interruptions. The extreme value is the lowest RMS line voltage measurement that was observed during the voltage dip or line interruption. As can be seen from the plot, ~ 75 % of voltage dips have an extreme value that is between 80 % and 90 % of the nominal line voltage. Note that in addition to the large number of minor voltage dips seen in the figure there was also a large number of "almost voltage dips" in the data, where the RMS line voltage briefly dropped to 91 % or 92 % of the nominal line voltage, but did not drop below 90 %.

One final thing to note about the way the faults are distributed is that some of the nodes that belong to the same DSO are very heavily correlated with each other. This means that the exact same fault often can be seen to occur simultaneously on two or more of the nodes belonging to the same DSO. E.g. a fault that is measured at the 66 kV level in the DSO's grid

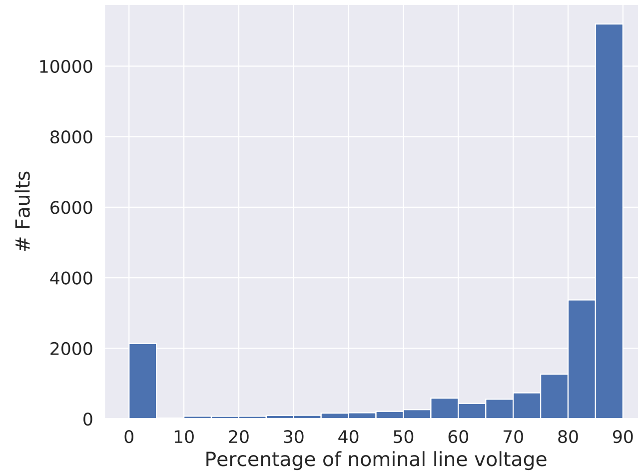

Fig. 6. Histogram showing the distribution of the extreme values of all voltage dips and line interruptions. The width of each bin is 5 %. The bin furthest to the right shows the number of voltage dips whose extreme value fell between 85 and 90 % of the nominal line voltage.

area will naturally propagate and be measured at measurement nodes in the downstream 22 kV grid.

III. Description of predictive model

As discussed in section II, ground faults and voltage dips show strong clustering behavior. Thus, the presence of a ground fault or a voltage dip means that there is a high probability that another voltage anomaly will occur soon. Thus it may be possible to predict more serious faults, such as line interruptions, based on the presence of less serious events such as voltage dips or ground faults. Furthermore, it would also be reasonable to suspect that voltage dips and ground faults may be predicted based on the presence of minor disturbances in the voltage that are too minor to be categorized as faults.

The idea behind the predictive model is to use information about the number and severity of minor voltage disturbances that occurred in the preceding 50 minutes to predict the probability that a fault is imminent. Minor disturbances in this context means any deviation from normal behavior that is not categorized as a voltage dip, ground fault or line interruption. E.g. a rapid voltage change, a dip in line voltage that is too small to be categorized as a voltage dip or a change in the relationship between the three line or phase voltages.

The model was trained on a balanced data set. The fault examples consisted of the minimum and maximum RMS line and phase voltages from between an hour to 10 minutes before a fault occurs, sampled at a frequency of 1 Hz. The time series did therefore not include the actual fault nor the last 10 minutes leading up to the fault. The non-fault examples were identical 50 minute long time series, except that they came from periods of time where no fault occurred in the next 24 hours, nor had occurred in the preceding 24 hours. Note that the dimension of each raw training sample, before preprocesssing, was 12x3000.

The model used was relatively simple. It starts by normalizing each of the voltage channels. Part of this involves setting

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the average RMS value during the first minute of the sample as the base value. For each voltage channel it then calculates the m largest deviations from this base value that occur during the remaining 49 minutes of the sample. It then differentiates the time series and calculates the n largest deviations from 0 for each voltage channels. The dimension of each prepossessed sample is thus $12 * (m + n)$. For the prediction results in the next section the values of m and n used were both 5.

The preprocessed sample is then fed into a random forest classifier [10] [11]. Scikit-learn's implementation of random forest with standard parameters was used [12]. The classifier decides what the probability is that this time series sample results in a fault.

Note that instead of using the line voltages V12, V23 and V31, the model instead uses V12, V23-V12 and V31-V12. The same was done for the phase voltages V1, V2 and V3. Note that this is the difference between the RMS values of the channels. This was done so that the model would be able to detect gradual changes in the relationship between the three channels during the 50 minute time period.

More advanced prepossessing techniques were tested, but they did not exhibit any noticeable improvements in performance and thus the simple method was retained.

IV. Prediction results

Figure 7 shows the ROC curves [13] for the random forest model when trained on three different data sets. The ROC curve is the true positive rate plotted against the false positive rate. The ideal result is that the area under the red curve (AUC) is 1. A model that is randomly guessing would receive an AUC of around 0.5.

The only difference between the three data sets is the variable t_{min}. This variable specifies that for a fault to be included in the data set, the time between the fault and the previous fault that occurred on any node belonging to the same DSO must be more than t_{min}. This variable was one minute in the plot on the left, an hour in the centre plot and 24 hours in the plot on the right.

With $t_{min} = 24$ hours the total number of faults in the data set that could be used for training and testing was reduced to 2786 from the original 69 612. However, this did not have a significant impact on the results, since the ROC curves in Figure 7 did not change significantly when increasing the number of fault and non-fault samples beyond 500 of each. To produce the figure, the size of the training set for each of the three plots was set at 1500 examples of faults, randomly sampled from the eligible faults, together with 1500 examples of randomly sampled non-faults. Testing was done using stratified 5-fold cross validation.

As we can see from the left hand pane in Figure 7, with $t_{min} = 1$ minute, ~ 35 % of the faults could be classified with high enough certainty for there to be a negligible amount of false positives. However this result could potentially be quite misleading. ~ 42 % of the fault samples in the data set with t_{min} = 1 min are ones where at least one fault occurred on the same node in the preceding hour. This is not the case for any of the non-fault samples. Thus, since the input to the model spans the period from 1 hour to 10 minutes before the fault occurs, samples where a fault occurs in this time period were trivially easy to categorize, leading to a misleadingly good ROC curve. For these samples, the model is not actually predicting that a fault is about to occur. It merely learns that if there is a fault in the input data, then this is a fault sample. Similarly, if no faults occurred in the time period between 1 hour and 10 minutes before the fault, but one or several did occur in the 10 minute to 1 minute time period, then the model is not predicting a fault ten minutes in advance, but between 0 and 9 minutes in advance, which is obviously easier.

If the model is instead trained and tested only on faults where $t_{min} = 1$ hour, it results in the ROC curve displayed in the centre of Figure 7. As the figure illustrates, the results have deteriorated considerably. The model does predict ~ 8 - 12 % of the faults with some confidence, however, out of the 100 samples that were assigned the highest probabilities of being faults, only 89 were actual faults and the remaining 11 were false positives. If t_{min} is increased to 24 hours, the models performance is reduced further, as can be seen in the right hand pane of Figure 7.

V. Discussion

In the process of developing and testing the model above, two major issues were identified. The first issue is that the data sets that the model was trained on were balanced. In an operational setting, a model like this may run continuously in the grid and produce an updated fault probability much more frequently than the occurrence of faults. As an example, the model could be run every minute and the fault frequency may be once every week. Thus, if the model does not have a very low false positive rate, the number of false alarms could very easily outnumber the true positives. Furthermore, since giving a false alarm to power operators could potentially be quite costly, even a relatively low false positive rate could be too high for a model to be applicable in the real world.

The second issue is that the time since the previous fault on the same node was identified as the dominant factor when estimating the probability that a new fault is about to occur. The probability of a new fault occurring declines rapidly as the time since the previous fault increases. Thus, a more relevant test of an operationally applicable model would be its ability to predict an upcoming fault with high confidence when no fault has occurred in a long time, e.g. in more than 24 hours.

The preferable way to test an early warning model for voltage anomalies would be to train and test it in a way that more closely mimics the way it would be used in an operational setting. Specifically; to test it on long continuous time series of historical voltage data from a specific node using a sliding window approach.

As can be seen in the right hand pane in Figure 7, the model does show some ability to predict around 5 % of faults in advance with some confidence when the previous fault occurred more than 24 hours ago, but the false positive rate was significant. Some testing using this model was done

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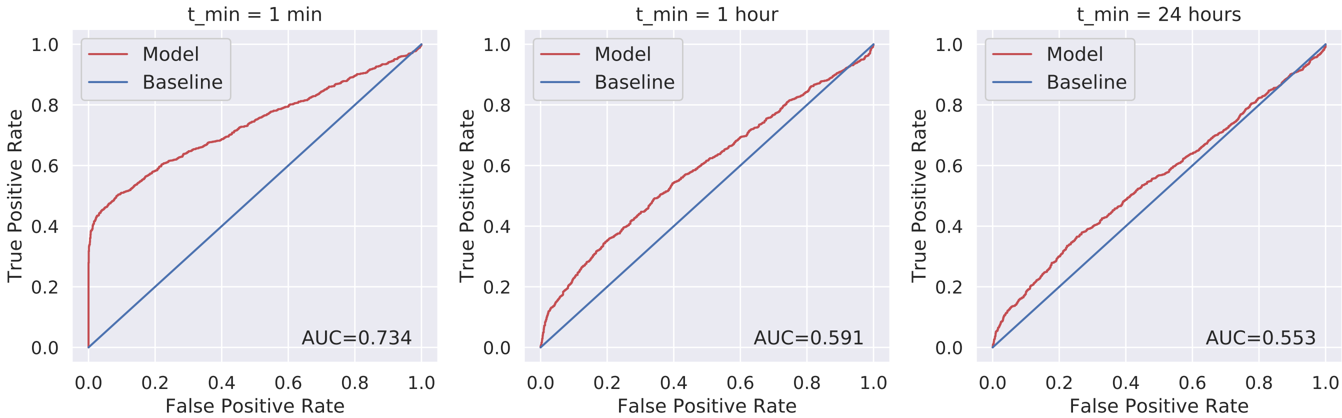

Fig. 7. From left to right: Change in fault prediction ROC curve when only looking at faults that occurred at least one hour, one minute or 24 hours after the previous fault event.

on longer historical time series. When tested using a sliding window approach, false positives typically outnumbered true positives. Such a model is therefore deemed to have too poor predictive ability to be used in an operational setting. A possible avenue of future improvement is to analyze whether some of the false positives share certain similarities that the model can be trained to learn to recognize, so that these false positives can be filtered out.

More research needs to be done on whether using the presence of minor disturbances to predict future voltage anomalies is feasible in an operational setting. Preliminary results so far seem to suggest that these minor disturbances occur frequently without being followed by major disturbances, and thus are not reliable indicators on whether a fault will soon occur or not.

Concerning faults that are separated by more than one hour from the previous fault on the same node, the overall observation both from the prediction results and from manual inspection of the PQA data is that a majority of the faults were not preceded by any early warning signs. That is, the progress of the time series in advance of the fault event typically tends to be more similar to the bottom plot in figure 2 than the top one. However a small percentage of these faults, somewhere around 10 %, did show clear signs in the preceding hour. This does give some promise to the idea that even though the majority of faults may not be predictable, it may be possible to predict a small percentage of faults reliably in advance. However, so far the number of false positives has been far to high for a model to be usable in practice.

VI. Conclusion

In this paper, it was observed that the probability of a new fault occurring as a function of the time since the previous fault appears to follow a roughly logarithmic curve in the time span between 1 second and 1 month. This tendency for temporal clustering among power quality anomalies is important to take into account when trying to predict the likelihood of future anomalies. Initial testing seems to suggests that the majority of voltage anomalies cannot be reliably predicted a long time in advance. However, more research needs to be done on whether it might still be possible to reliably predict a small percentage of them. Finally, training on balanced data sets is a training methodology that is not representative for operational conditions, and thus less applicable for evaluating voltage anomaly prediction models.

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