Detecting the linear and non-linear causal links for disturbances in the power grid

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Abstract. Unscheduled power disturbances cause severe consequences for customers and grid operators. To avoid such events, it is important to identify the causes and localize the sources of the disturbances in the power distribution network. In this work, we focus on a specific power grid in the Arctic region of Northern Norway that experiences an increased frequency of failures of unspecified origin. First, we built a data set by collecting relevant meteorological data and power consumption measurements logged by power-quality meters. Then, we exploited machine-learning techniques to detect disturbances in the power supply and to identify the most significant variables that should be monitored. Specifically, we framed the problem of detecting faults as a supervised classification and used both linear and non-linear classifiers. Linear models achieved the highest classification performances and were able to predict the failures reported with a weighted F1-score of 0.79. The linear models identified the amount of flicker and wind speed of gust as the most significant variables in explaining the power disturbances. Our results could provide valuable information to the distribution system operator for implementing strategies to prevent and mitigate incoming failures.

Keywords: Energy analytics · Anomaly detection · Power quality metering · Unbalanced classification

1 Introduction

Unscheduled power distribution disruptions are often a major problem for customers and grid operators since they affect everyone connected to the power grid from single households to large industrial players [8, 16, 18, 27]. The distribution system operator (DSO) is contractually obliged to provide a reliable power supply and compensate customers affected by any possible power interruptions [17]. For the end-use customers, power failures might have complex and adverse socio-economic consequences in communities that are heavily reliant on the electricity supply to satisfy their needs [29, 13]. To satisfy the customer's requirements, the DSOs must implement the energy management plans that account for the technology, and the infrastructure required to meet the expected demand.

In this study, we focus on a specific power grid in the Arctic region of Northern Norway where the successful transformation of the local food industries into an international company has caused a huge increase in electricity demand. The industry is characterized by fish processing activities that are highly seasonal and that require stable power quality due to the presence of many automatized machines in the production line. Even minor power disturbances in the power supply trigger significantly long interruptions since the whole production line needs to be reset. In particular, for every short-term power interruption that occurs, 40 minutes to 1 hour might pass before resuming production.

The consequences of the power disturbances are exacerbated by the topology of the energy network under analysis, which has radial distribution. Therefore, it is important to develop strategies to increase the reliability of the power grid that ensure the growth of local industries.

One way to improve the reliability of the power distribution is to build a new power grid that can handle larger power demand. However, this is costly, time-consuming, has a huge environmental impact, and contradicts the vision of better utilizing the current electricity grid infrastructure[1] [23]. An alternative solution is to limit the failures and strengthen only the most vulnerable parts of the grid, but this requires to first identify the factors triggering power interruptions.

The identification of causing factors for failures in the power grid has proven to be a major challenge for the DSO [27]. However, the increased availability of energy-related data makes it now possible to exploit advanced data analytics techniques that allow to develop strategies to improve the reliability of the power grid [26, 7, 15, 11, 4–6]. Recent studies based on statistical data analysis and machine learning (ML), indicated that extreme weather conditions are often the major cause of failures in the power grid [22, 25, 28, 20, 10, 19]. However, it is likely that other factors than weather conditions could affect the power quality. The impact of the increased strain on the power grid as a consequence of the increased electrification in the society were investigated in [2]. The study in [14], proposed a methodology to predict power failures by analyzing data from advanced electricity meters. The authors concluded that incipient power interruptions are easier to predict than earth failures and voltage dips. The challenge

[1] https://www.miljodirektoratet.no/publikasjoner/2020/januar-2020/klimakur2030/

of detecting earth failures was addressed in [1], which proposed a solution to detect failures by using a specific power distribution system simulator.

Most of the studies mentioned so far are proof of concepts and the results are shown on synthetic data or benchmark power systems. In this work, we tackle a real-case study and we explore a wider spectrum of potential causing factors for power failures. We consider explanatory variables that are divided into two groups: meteorological and power consumption data. We exploit ML techniques to detect the power disturbances and to identify the most explanatory features among high-resolution power-quality metering data and weather variables.

This paper extends our previous study, which analyzed failure data from the year 2020 [12]. Previously, we exploited statistical and ML techniques to detect the causes of power interruptions and identified wind speed of gust and local industry activity to be the main controlling parameters. However, there were important limitations in the data collected in the 2020 failure-detection study:

1. The machinery of the local industries connected to the power grid is so sensitive to the power quality that they experience failures that are not registered in the failure-reporting system of the DSO. Since DSOs are contractually obliged to provide a reliable power supply to all their customers, is fundamental for them to gain better insight into the actual power quality to fill the gap between the customer's experiences and the DSO.
2. The resolution of data in 2020 was too low (1-hour) to get detailed information about how power consumption truly affects power quality.

To address these issues, new power quality meters were installed 19 February 2021 in the particular location of interest. These meters log data every minute, register every small voltage variations, and provide fundamental information (the specific phase where the failure is registered on, the magnitude of voltage variation, the amount of transients and flickers) about the current quality in the power grid. As shown in the experimental results, standard ML techniques for classification allow to detect most of the power disturbances, showing that high-resolution data from power quality meters in conjunction with weather data are highly informative variables to detect and localize power disturbances. Finally, by looking at the parameters of the linear classifiers, we rank the variables that are the most important in explaining the power disturbances.

2 Case study and reported failures

2.1 Investigated power grid

The power grid analyzed in this study is a radial distribution system serving an Arctic community located approximately at (69.257°N, 17.589°E). Arva Power Company, the DSO of the power grid, has named this specific grid as SVAN22LY1 [3]. Fig. 1 shows a overview of the whole SVAN22LY1 grid, indicated by green dots. The SVAN22LY1 grid spans over 60 kilometers from south

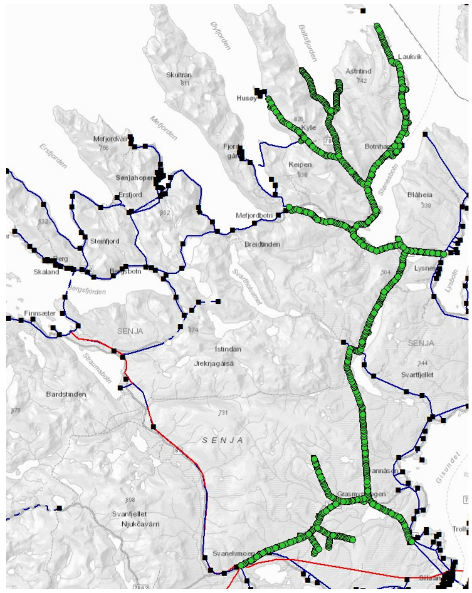

Fig. 1. The SVAN22LY1 power grid. The power is distributed towards the north from the south. Each green dot represents a unique position of a utility pole.

to the northernmost point and has several branches to various communities towards the north. There are 978 unique utility poles (marked by green dots in Fig. 1) that support the power lines. The black boxes in Fig. 1 represent the electric transformer stations connected to the power grids. The red lines represent a power grid with an operating voltage of 66 kV, while the blue lines represent a power grid with an operating voltage of 22 kV. The SVAN22LY1 radial grid covered by green dots has a operating voltage of 22 kV [3]. The largest customers connected to the SVAN22LY1 grid are located at the end of the northernmost point of the radial.

The total energy demand in the Arctic community where the grid is located is dominated by the load consumption of the local industry. The industry has electrical machines that are sensitive to stable power quality and a minor disturbance in power quality could bring the production line to halt.

2.2 Reported failures

The reported failures used in this study is logged by a power-quality (PQ) metering system. In our former study on failure detection [12], the failure data was based on a metering system that reports failures from substation monitoring. That metering system only reports events failure events when there is a power outage (90% drop in voltage magnitude from normal) on all phases in the three-phase system. However, machines are very sensitive to instabilities in the power quality and even a minor disturbance in voltage magnitude could result in production stop. Consequently, there was a mismatch between the logged failures in the substation monitoring system, and what is being experienced by the local industries.

To address this issue, in February 2021 the Arva power company installed a PQ metering system in proximity of the local industries to continuously measure the power quality. The PQ metering system reports all incidents with a voltage variation of $\pm 10\%$ from the nominal values on each phase of a three-phase system with phases A, B, C. According to the standard definition, all variations of $\pm 10\%$ from normal conditions are defined as a voltage variation and a drop larger than 10% is referred to as a voltage dip [9]. Voltage dips could provoke tripping of sensitive components such as industrial machines. For the DSO, it is fundamental to identify the causing factors for such voltage dips to implement strategies to prevent and mitigate incoming failures.

3 Methodology

To identify the causing factors for the failures in SVAN22LY1, several potentially interesting variables are collected. The variables can be divided into two groups, weather-related and power-related failures, and are described in detail in the following.

3.1 Weather measurements

The weather variables that are considered relevant in causing power failures are: wind speed of gust, wind direction, temperature, pressure, humidity, and precipitation. Similarly to our previous study [12], the weather data are collected from areas that are more exposed to harsh weather conditions, such as hills and cliffs near the sea coast. To collect the weather-data in the Arctic region of interest, we used the AROME-Arctic weather model [2]. This model is developed by the meteorological institute of Norway (MET) and provides reanalysis of historical weather data since November 2015 with a spatial resolution of 2.5 kilometers and a temporal resolution of 1 hour. To import the variables, we use the coordinates from the weather exposed areas as input to the AROME-Arctic model.

3.2 Load measurements

It is reasonable to assume that some types of failure are not caused by weather phenomena, but originates by external factors that influence the power flows on the grid. To model these effects, 6 different power-related variables from the largest industry connected to SVAN22LY1 are collected. The variables selected as relevant to explain power failures are: difference in frequency, voltage imbalance,

[2] https://www.met.no/en/projects/The-weather-model-AROME-Arctic

difference in active and reactive power, minimum power factor, and, finally, the amount of flicker in the system. All variables are metered on three different phases (phases A, B, and C).

A *change in the power frequency* could be caused if there is an imbalance between energy production and consumption in the system. If there is a change in the power frequency (50 Hz is the normal frequency), the imbalance could cause power disturbances for the end-use customers.

Voltage imbalance is a voltage variation in the power system in which the voltage magnitudes or the phase angle between the different phases are not equal. It is believed that rapid changes (big changes within seconds/minutes) in power consumption at large industries could affect the power quality. Therefore, the *difference in active and reactive power* for each phase within each minute is computed. If the difference is large, there is a high activity at the industries, which are reported by the locals to result in larger probability for failures.

The *minimum power factor* represents the relationship between the amount of active-and reactive power in the system. If the minimum power factor is low, there is increased amount of reactive power in the system. In the end, the amount of flicker in the system are collected.

Flicker is considered as a phenomena in the power system and are closely connected to voltage fluctuations over a certain time frame [24]. A voltage fluctuation is a regular change in voltage that happens when machinery that requires a high load is starting. In addition, rapid changes in load demand could cause voltage fluctuations. If there are several start-up situations, or the load varies significantly during a given time frame, it will be measured a high amount of flicker in the system. The amount of flicker is particularly relevant in the industry considered in this study, as they have several large machines that require high loads and have a cyclical varying load pattern. In this study, the time frame of the flicker is 10-minutes, which is the standard for measuring the short-term flicker [17].

The resolution from the PQ metering system are in a 1-minute resolution with real-time logging of failures. To streamline the presentation of our findings, only the results from phase A are visualized since there are no significant differences with the observations from phases B and C.

3.3 Dataset construction

The final dataset consist of 6 different energy-related variables and 6 different weather variables. The variables analyzed are summarized in Tab. 1.

Once the dataset with all variables is constructed, we model each data sample as a pair $\{\mathbf{x}, y\}$, where $\mathbf{x} \in \mathbb{R}^{12}$ is a vector containing the value of the 12 features at a given time and y is a binary label indicating if a power failure occurred ($y = 1$) or if the power grid operates at normal conditions ($y = 0$). The binary variable divides the dataset into two classes: a minority class, the failures, and a majority class, the non-failures, i.e., normal conditions.

The PQ metering system have 1-minute resolution, while the weather data have 1-hour resolution. To align the temporal resolution of the different types

Table 1. Variables analyzed to detect failures in the SVAN22LY1 power grid

Feature ID	Weather variables
1	Wind speed of gust
2	Wind direction
3	Temperature
4	Pressure
5	Humidity
6	Precipitation
	Power variables
7	Difference in Frequency
8	Difference in Voltage imbalance
9	Difference in Active Power
10	Minimum Power Factor
11	Difference in Reactive Power
12	Flicker

of variable, the power consumption data are sub-sampled by taking one sample every 60. As an alternative sub-sampling technique, we tested taking the average of the values within each batch of 60 consecutive samples of power measurements. However, the results did not change significantly and, therefore, the former sub-sampling method was used. In the final dataset, there are 90 samples with $y = 1$ representing reported failure (10% drop and below in voltage magnitude), and $1,647$ samples with $y = 0$ representing normal conditions without any power disturbance.

3.4 Classification strategy

In this study, we frame the failure detection in the SVAN22LY1 grid as a classification problem and test different linear and non-linear classifiers. All models are implemented in Python with the scikit-learn library [21].

Linear classifiers. The first linear model is a Ridge regression classifier, which first converts the target values into { -1,1} and then treats problem as a regression task. The second model is Logistic regression, which uses a logistic function to predict a binary variable. The third model is the Linear Support Vector Classification model (LinearSVC), which is a type of Support Vector Machine (SVM) with a linear kernel.

Due to the strong class imbalance, we configure each model to assign a class weight that is inversely proportional to the number of samples in each class. In this way, errors on the underrepresented class are penalized much more than errors on the larger class, which in our case represent the nominal condition. The linear models are configured using the default hyperparameters in the scikit-learn implementation.

One advantage of using linear classifiers is that they construct a decision boundary directly in the input space, which allow to easily interpret the decision process of the classifier. The linear models assign a weight w_i to each feature x_i in the input space: the higher w_i, the more the values of x_i impact the classification outcome. Therefore, looking at the magnitude of the weights w_i is a simple strategy to estimate the features importance for the classification task.

Non-linear classifiers. We use three different non-linear classifiers. The first two are an SVM classifier with class weight proportional to class size, and an one-class SVM classifier. Both SVM classifiers are equipped with a radial basis kernel function. In addition, we use a Multi-layer perceptron (MLP) as the third classifier.

Non-linear models are generally more sensitive to the selection of the hyperparameters. For the SVC classifier, we optimize the kernel width γ and the regularization parameter C, which is the weight of the L_2 penalty. For the one-class SVM, we optimize the kernel width γ and ν, a parameter that balances the training errors and the number of support vectors. Finally, for the MLP classifier we use ReLU activations, the Adam optimizer with initial learning rate $1e-3$, and batch size 200. The hyperparameters that are optimized in the MLP are the number and size of the hidden layer and the weight of the L_2 regularization term.

Model selection and performance evaluation. To evaluate the model performance we first shuffle the data and then perform a stratified k-fold, with $k = 5$. In each fold, 80% of the data are used for training and the remaining 20% is used as test set. Before training the models, the input values $\mathbf{x}$ are normalized by subtracting the mean and dividing by the standard deviation computed on the training set. The training set is used to fit the model parameters by minimizing the classification loss. Once the optimization procedure has converged, its performance is evaluated on the test set. The average classification performance obtained on the 5 folds is reported as the overall performance of the classification model.

Measuring classification performance. The classification performance is measured by looking at the confusion matrix, which reports the following quantities: True Negatives (correctly identified non-failures), False Positives (predicted failures, while no failures happens), False Negatives (misses a failure), and finally the True Positives which is the number of failures correctly identified.

To quantify the performance with a single value we use a weighted F1 score:

$$F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} = \frac{\text{TP}}{\text{TP} + \frac{\text{FP}+\text{FN}}{2}}, \tag{1}$$

where TP, FP, and FN are the true positives, false positives, and false negatives, respectively. Due to the strong class imbalance, in this study we compute a weighted F1 score, i.e., we weight the F1-score obtained for each class by the number of samples from that class and then we compute the average.

4 Results

4.1 Classification scores and feature selection

The performance achieved by each classificator are reported in Tab. 2 in terms of average Weighted F1 score and the average number of TN, FP, FN, and TP obtained across the 5 folds. Note that the TN, FP, FN, and TP are rounded to the closest integer.

Table 2. Classification score for different models

Classifier	TN	FP	FN	TP	Weighted F1 score
Linear					
Logistic Regression	273	56	4	13	0.775
Ridge Classifier	271	58	4	14	0.792
LinearSVC	272	57	4	13	0.788
Non-linear					
SVM	273	56	3	14	0.804
One-class SVM	2	327	2	15	0.591
MLP	325	3	6	12	0.793

The classification results show that there are no strong differences. The non-linear SVM classifier achieves top performance with a weighted F1 score of 0.804, followed by the MLP and the Ridge Classifier that achieve weighted F1 scores 0.793 and 0.792, respectively. Interestingly, the one-class SVM performs worse than any other model in terms of weighted F1 score, as it finds way too many FP but, on the other hand, is the model that finds the least FN on the test set. In the case study focused in this work, the main goal is to detect as many failures as possible, meaning that solutions with very few FN (missed detection of power failures) should be preferred. However, there is still a tradeoff to be made with the percentage of FP, i.e., the false alarms. Obviously, a model that classifies everything as a power failure is not useful in practice.

Finally, it interesting to notice that linear and non-linear models achieve similar performance. This suggests that the two classes are mostly linearly separable, i.e., most of the data samples can be separated reasonably well by an hyper-plane in the input features space. On the other hand, the data samples that are misclassified are likely very overlapping across the two classes and is very difficult to find a decision boundary, even if is non-linear, that can correctly separate them. The good performance of the linear models motivates the feature selection procedure discussed in the next section.

Feature selection. As discussed in Section 3.4, looking at the magnitude of the weights attributed by the linear models to the input features allows us to identify the features that contribute the most to determine the correct class. In return, this can give us insights about which variables explain the most the occurrence of failures in the power grid.

Fig. 2 reports the magnitude of the weights assigned to each feature after each linear model is trained. The higher the magnitude weight of a given feature, the more such a feature is important in predicting the class.

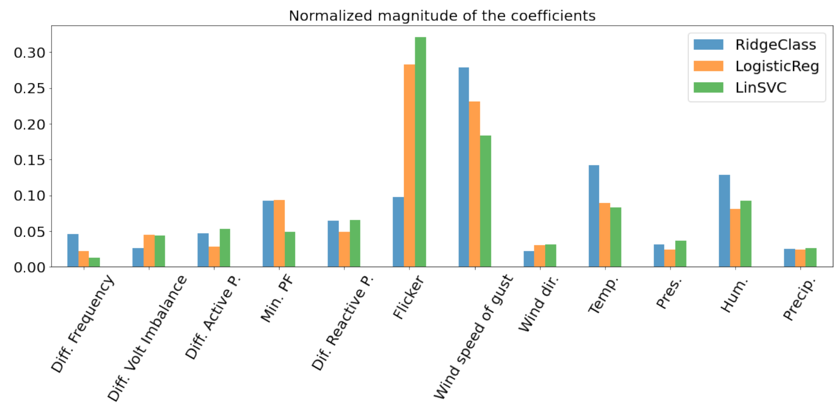

Fig. 2. Coefficients' magnitude assigned to each feature by different linear models. High magnitude indicates that the corresponding feature is important.

From Fig. 2, we observe that in each model the *Wind speed of gust* variable is always associated with a weight with large magnitude. The Linear SVC and the Logistic Regression classifiers attribute a large importance also to the *Flicker* variable, while the Ridge Regression classifiers weights the other features more uniformly and assigns weights to *Temperature* and *Humidity* that are slightly larger than the weight assigned to *Flicker*.

Overall, we can conclude that both the industry activity and the weather effects are important in discriminating between the failure and non-failure class. The most important of the power-related variables seems to be *Flicker*, while the *Wind speed of gust* is consistently the most explanatory weather-related variable according to each linear model. Our results are aligned with experiences of the DSO and the local costumers, as more failures seem to occur when there is high activity at the industries and the machines operates at full load. In addition, it has been noted that failures are more likely to occur when there is strong wind, which could create collisions in the cables of the power lines.

5 Conclusions

In this work, we tackled the problem of detecting unscheduled failures in the power grid, which have major consequences for the local industries that are experiencing an increased frequency of failures. In collaboration with the DSO, totally 12 different variables were collected (6 weather-related, and 6 energy-related). Through a features selection procedure based on data-driven classification, we identified the variables that mostly explain the onset of power disturbances. Our results indicated that the amount of flicker and wind speed of gust as the most significant variables in explaining the power disturbances. This represents valuable information to the DSO for implementing strategies to prevent and mitigate incoming failures.

Despite the baseline classifiers used in this study managed to correctly detect most of the power failures reported (up to 75-80%), they produced several false positives. While, false positives are less critical in this particular application, more advanced classifier will be investigated in future work to improve the results, as well as strategies to interpret the decision process of non-linear classifiers.

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