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SUPERVISED LEARNING FOR FAULT CLASSIFICATION USING HYBRID TRAINING DATASETS

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ABSTRACT

Electrical faults in the distribution system can lead to interruptions in customer power supply resulting in penalties that are borne by the distribution system operator. Accurate fault classification is an important step in locating the fault to achieve faster network restoration times. This paper presents a classification model in two parts: one determines the degree of stability in the fault waveforms and the second uses a machine learning model to classify real-world faults based on the number of fault phases. A set of business rules are developed to characterise instability by performing a windowed Fourier analysis and studying the strength of the fundamental frequency component of fault waveforms. Results show that the developed SVM model can differentiate between real-world instances of single-phase, two-phase and three-phase stable faults with a classification accuracy of 95%. Additionally, we show that adding a small subset of synthetically developed faults to the training data improves classification accuracy.

INTRODUCTION

A responsibility of DSOs (Distribution System Operators) is to find the location of electrical faults in the network and restore the disrupted network. Identification of the fault type (between single-phase, two-phase, and three-phase faults) is necessary for finding its location as it determines the how the fault-loop impedance is calculated. This fault-loop impedance is then used in localisation calculations by network analysis tools. Misclassification of faults results in the calculation of the wrong loop impedance which adversely affects the fault localisation, thereby making fault classification an important aspect of a DSO's activities [1].

Modern research on fault analysis involves studying fault waveforms. This is primarily done through the lens of Fourier and wavelet transforms [2]. The Fourier Transform details which frequencies constitute the original fault signal, however, it does not localise this formation in time, unlike the wavelet transform [3]. The wavelet can capture both short high-frequency components and longer low-frequency components using a filter called the "mother wavelet" [2][4].

In addition, machine learning (ML) has been emerging as a popular method to classify fault signals. Among different ML-based fault classification methods like decision trees, k-nearest neighbour, support vector machines (SVM), and artificial neural networks, SVMs were found to be the most accepted technique. This is because SVMs strike a balance between the high interpretability of decision trees, and the superior processing power of neural networks [5].

A general challenge for waveform-based fault classification is encountered when the measured waveforms are not sufficiently sinusoidal. Such faults are designated as unstable and carry a higher risk of misclassification. Identifying unstable faults before attempting classification can reduce the risk of incorrect fault localisation and switching off the wrong network section [6].

This paper presents a two-step methodology combining the use of Fourier and wavelet transforms for signal processing, and SVM for classification, with the following specific contributions:

1. A method based on windowed Fourier transforms is introduced to identify unstable faults.
2. An SVM-based ML model is shown to classify (stable) real world faults with an accuracy of 95%.
3. It is shown that the classification performance improves when a small number of synthetically developed single-phase, two-phase and three-phase faults were added to the sample space of recorded faults.

PROPOSED APPROACH

Faults can be categorised on the basis of the number of faulted phases, and the stability of the waveforms. This study uses digital fault recordings (DFRs) from the SASensor, a substation automation tool deployed by the Dutch DSO Alliander. The SASensor records fault waveforms at a rate of 4 kHz, starting from 1*s* before the fault incidence up to a few seconds after the fault extinguishes. Accurately labelled DFRs were used as one of the data sources for this study

There are two underlying steps to the fault classification procedure -- the determination of the degree of stability with the use of Fourier transforms, and the determination of the type of fault (single-/two-/three-phase). An overview of the developed two-step methodology for fault signal classification can be seen in Figure 1.

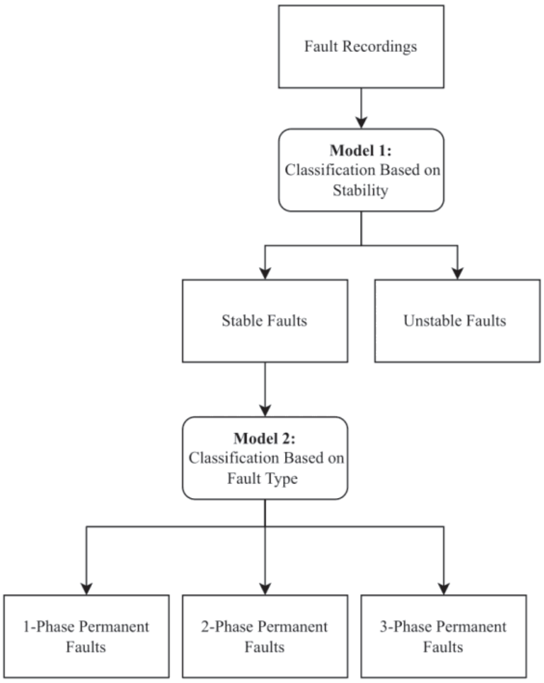

Figure 1. Framework for electrical fault classification.

The two classification blocks represent the stability analysis and the subsequent test for the number of involved phases in the fault. For classification purposes, stable faults are permanent faults that can automatically be classified correctly based on the number of phases. We use the degree of the presence of the 50 Hz frequency (or the lack thereof) in fault waveforms to classify them as stable or unstable using a stability classification model. The output of the first step is a set of stable (and hence permanent) faults. In the second block, the faults are classified based on the number of fault phases using an SVM model that performs a classification based on features extracted from the DFRs. Both models are described in detail in the following sections.

The fault classification model is trained on features that are extracted from manually labelled fault recordings (supervised learning). This set of real fault recordings is of limited size, but accurately represents the diversity of faults encountered. In addition, we investigated the value of enriching the data set with synthetic DFRs that accurately characterise textbook single-/two-/three-phase permanent faults. The fault data for the synthetic faults were created in the same format as the SASensor fault recordings. Doing so enlarges the size of the training data set and accuracy for textbook faults, but may come at the expense of accuracy for real world faults. Results from a quantitative comparison are presented below.

STABILITY CLASSIFICATION MODEL

An unstable fault, as defined by Gu et al. in [6], is a fault whose current/voltage is not sufficiently close to a sinusoidal waveform. An example of an unstable fault can be seen in Figure 2.

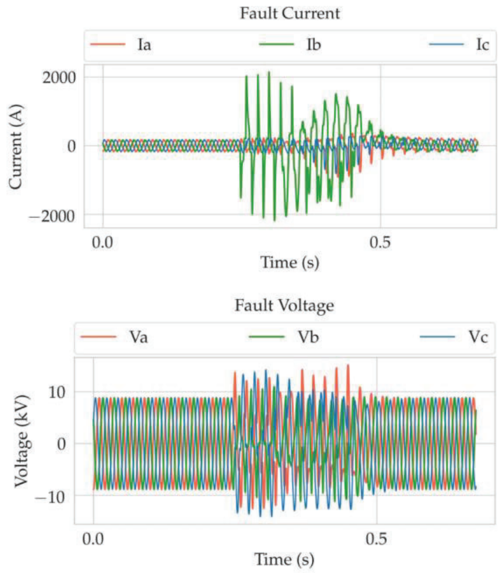

Figure 2. Current (top) and voltage (bottom) waveforms for a single-phase unstable fault.

Features and threshold values to identify unstable faults were proposed by Gu et al in [6]. From practical experience, it has emerged that these thresholds are too strict: faults that can be classified as stable permanent or self-extinguishing, are sometimes identified as unstable. When faults are classified as unstable, their locations are not automatically calculated to avoid the risk of sending a wrong location to the control centre for isolation. Improving the criteria for stability can therefore increase the number of correct fault locations sent to the control centre.

The objective is hence to enable the automatic classification of these unstable permanent faults and to add more certainty to what makes a fault (un)stable. While it is important to ensure stable faults are not classified as unstable, it is also vital to ensure that the definition does not leave room for additional misclassifications.

Windowed Fourier Analysis for Detecting Instability

The Fourier transform was used to analyse and select features in the frequency spectrum of the faults that were classified as unstable. This method connects the notion of “insufficiently" sinusoidal behaviour with unstable faults using a windowed analysis of the fault waveforms. The stability of a fault waveform was studied by identifying sinusoidal periods. For a signal to be considered stable, and

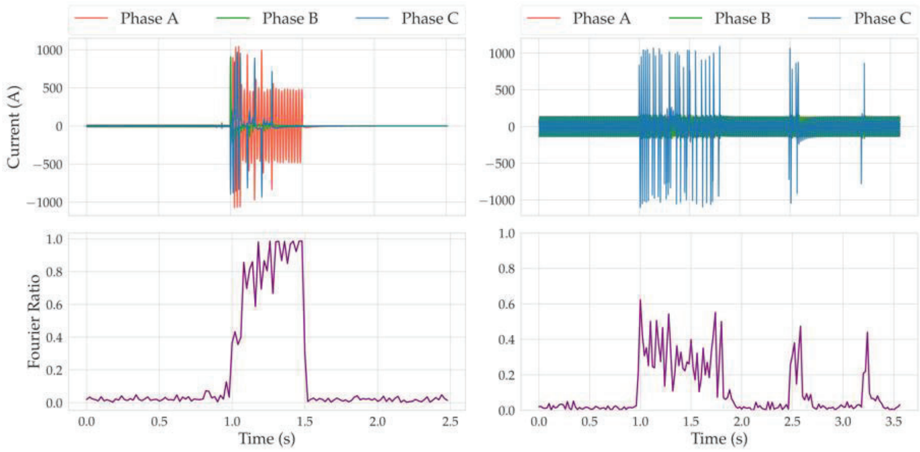

Figure 3. Comparison of the 50 Hz Fourier component of unstable single-phase permanent (left) and single-phase self-extinguishing (right) faults.

for accurate fault localisation, practical experience suggests that at least two consecutive stable periods must be present [6]. The stability was hence studied period-by-period with a moving window of one cycle (80 samples). The zero-sequence component of the fault waveform was used to highlight the fault periods.

The derivative (two-sample difference) of the zero-sequence current was calculated for each fault to accentuate distortions and transients. A metric F_{ratio} is defined to quantify this degree of instability for each window:

$$F_{ratio} = A_{fault} \,/\, A_{ref} \quad (1)$$

Where A_{fault} is the strength of the 50 Hz component of the derivative of the zero-sequence current for a cycle of the fault current, scaled to have a unit RMS (root mean square) value. Reference metric A_{ref} is set to the 50Hz component of a reference sinusoidal signal with unit RMS value. For two signals with equal RMS value, the amplitude of the 50 Hz Fourier component of the fault waveform will always be less than or equal to that of the reference sinusoidal waveform due to the presence of distortions. Therefore, $F_{ratio} \leq 1$, with equality holding only for a perfectly sinusoidal waveform. Hence, this developed metric F_{ratio} can be used for assessing the relative sinusoidal nature of the fault waveform. F_{ratio} is calculated for each period of the fault current waveform, enabling a period-wise analysis of stability.

Development of the Stability Classification Model

The results of this moving window analysis of the 50 Hz component for a sample permanent and extinguishing fault can be seen in Figure 3. In the case of the permanent fault, it can be observed that, at the initiation of the fault, the distortions in the waveform reflect in the magnitude F_{ratio}. In the case of the self-extinguishing fault, it can be observed that the values of F_{ratio} are significantly lower than that of the permanent fault for all periods of the fault.

A set of features from the F_{ratio} series for each fault were identified: the maximum value (f_{max}), the mean (f_{mean}), the standard deviation (f_{stdev}), and the number of cycles for which the Fourier comparison waveform is greater than a threshold ($f_{periods}$). A scoring system was developed to assess how many counts the fault features comply with the criteria for stability. The criteria for stability were the values that resulted in the highest accuracy scores on the training set, determined for each criterion separately using 5-fold cross validation. The threshold values are as follows: $f_{max} > 0.8$, $f_{stdev} > 0.123$, $f_{periods} > 2.5$, $f_{mean} > 0.011$. Faults are scored for stability according each criterion, and the total score can give can be used to assess the overall stability of the fault.

FAULT TYPE CLASSIFICATION MODEL

The second step of the classification process is the development of a model that can distinguish between 1-phase, 2-phase and 3-phase faults. The support vector machine (SVM) model with a radial basis function was chosen as the classifier due to its ability to classify non-linearly separable classes [7]. The model hyperparameters for an SVM are C and γ. The hyper-parameters that were selected from the results of performing a 5-fold validation process on the SVM are $C = 100$ and $\gamma = 1$.

An initial set of 36 features was extracted from the 3-phase fault voltage and current waveforms. Discrete wavelet transforms (DWT) using the Daubechies-4 filter were used to decompose the signals into smaller frequency bands. Since the sampling frequency is 4kHz, the highest frequency that can be captured is 2 kHz. Therefore, detail

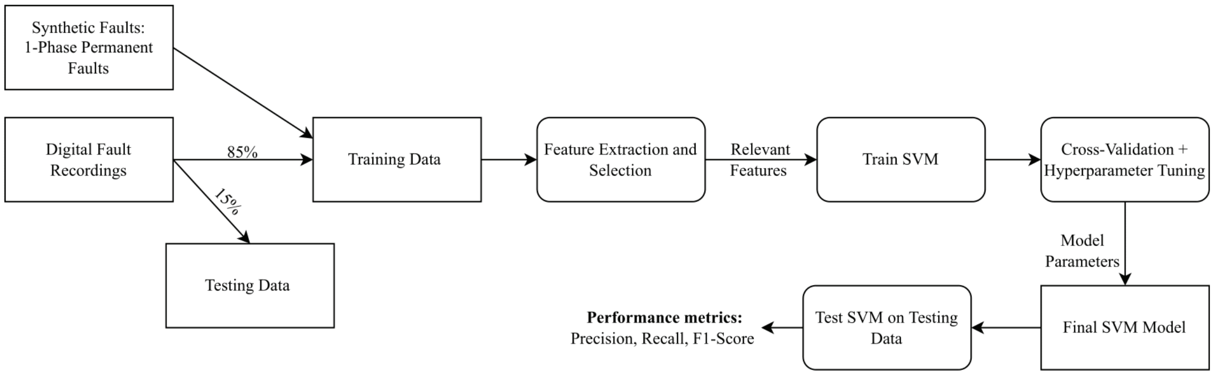

Figure 4. Block diagram showing the working of the ML fault classification model.

coefficients from the first two levels of decomposition, in 1 kHz - 2 kHz and 500 Hz - 1 kHz bands were considered to be the most pertinent for the study based on expert knowledge of which frequency bands carry the transient frequencies. In addition to these features, a set of features extracted from the signal in time, such as the peak and standard deviation were considered.

To narrow down on the most pertinent features from the initial 36, the ANOVA technique was used for ranking the features in order of their importance and the selection of the number of features was done using 5-fold cross-validation. The final 8 features include metrics that compare the RMS values of the phase currents, standard deviation of the zero-sequence voltage and current, and the energies of the detail coefficients of the fault current waveform at the two aforementioned frequency bands. The optimal feature count was the one with the best average of the cross-validation accuracy score of each fold.

RESULTS AND DISCUSSION

Fault Stability Analysis

This section discusses the results of applying the developed rules to the test set. The test set consists of 51 faults that were labelled as *unstable* faults by the stability rules in [6], currently in use at Alliander. Since the older method of fault detection sometimes classified stable faults as unstable, the business rules defined in this chapter attempt to improve the definition of (in)stability, by increasing the rate of identification of faults that are stable, i.e., to increase the number of 'true positives' of stable faults so they can be correctly isolated from the rest of the network.

The rules classify faults based on their stability as being either definitively stable, definitely unstable, or "requiring manual inspection". This final class consists of faults that have the possibility of being stable through expert inspection. The rules were applied to classify the test set at hand and the results are presented in Table 1. It can be observed that 10 faults have been classified as being definitively stable.

This implies that within the subset of faults classified as unstable, there are characteristics from the moving-window Fourier analysis that can indicate that these faults are actually stable. Additionally, by indicating which faults do and do not need manual inspection (and to what degree of certainty), this model can also help prioritise the manual inspection efforts.

Table 1. Results of the classification of unstable faults based on their stability.

	Stability Decision		
	Stable	Inspect Manually	Unstable
Number of Faults	10	23	18

Fault Classifier Analysis

The performance of the classifier was evaluated using different data sets for training and testing. The input data for the model consists of "real" faults that were recorded in the distribution network, and synthetic faults that were generated to represent ideal faults. By training and testing on different subsets of the real and synthetic faults, it is possible to determine the extent to which the ability of the classifier to generalise from the training set. The test cases used to assess the performance of the classifier are presented in Table 2. In view of the real-world application, real-world data was always used for testing.

In the first test case, the SVM classifier is trained on all the synthetically created faults and tested on the real-world single-phase, two-phase and three-phase faults. It is expected that the performance of the classifier in this test would depend on the extent of dissimilarity between practical fault instances in the distribution network and the synthetic faults. This test case is useful for understanding how much can be learnt by the classifier from the synthetic faults, and how relevant these features are to actual faults in the distribution network.

Table 2. Description of the test cases used to assess classifier performance.

Case	Training Data	Test Data
I	Synthetic	Real-world
II	Real-world	Real-world
III	Synthetic + Real-world	Real-world

In the second test case, the classifier is trained and tested on the real-world faults. The data set is split in a ratio of 85:15 for training and testing respectively. The results of the performance of the classifier in this test case provides information on whether the model learnt discriminating information from the current set of real faults to accurately classify future real faults.

In the third test case, the synthetic singe-phase, two-phase and three-phase faults are added to the real-world training data. This is done to add stronger reference waveforms for the practical faults to improve the ability of the classifier to generalise.

Table 3. Comparison of the performance of the SVM fault type classifier in different test cases.

Case	Precision (%)	Recall (%)	F1-Score (%)
I	86	84	84
II	91	90	90
III	95	95	95

The performance results are summarised in Table 3. While training on the synthetic faults alone (in case I) provides understandably less than desired results, as the synthetic faults do not have the distortions that occur in actual faults in the network. The performance improves significantly when the model is trained on real-world data (case II), and further improves when synthetic fault data is added to the training set. The latter is perhaps surprising, as the distribution of features of real-world and synthetic faults differs (covariate shift), which generally reduces classifier performance. However, the synthetic data also increases the training data set and the additional reference values ultimately improve the model's performance substantially. This has useful practical applications in situations where synthetically developed signals can be used to enrich training data sets to improve classifier performance.

CONCLUSION

In this paper, two classification models were developed – one to classify faults based on their stability, and the other to classify faults based on the number of fault phases. It was found that the relative strength of the fundamental frequency component is useful in characterising the stability of fault signals by highlighting the disturbances in the signal. An SVM was developed to classify faults according to the number of participant phases. With the *addition* of synthetic faults to the real-world training data set, the classification accuracy improved substantially. This shows the significant potential value of even simple synthetic training data when used to train ML models in environments with limited real-world training data.

Currently, the analysis of stability was restricted to the classification of single-phase unstable faults due to the limited dataset for multi-phase instable faults. In order to diagnose instances of multi-phase instability, a future direction could be to extend the scope of the classifier.

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