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INTERMITTENT EARTH FAULT DETECTION IN DISTRIBUTION NETWORK BASED ON THE VOTING CLASSIFICATION TECHNIQUE

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ABSTRACT

Intermittent earth faults in non-effectively distribution networks, especially with underground cabling, can compromise the quality of the electricity supply. This type of earth fault may be followed by permanent faults, which in turn puts the networks on the line. This phenomenon monitoring can help distribution system operators (DSOs) to plan maintenance to reduce system interruption and improve MV electricity delivery. Thus, this research will examine AI-driven approaches, which are suitable for complicated issues, to improve distribution power grid monitoring and maintenance. The research focuses on medium and low-voltage grids and applies the voting classification technique (VC) to monitor and predict earth faults. Moreover, IEC 61850 Sampled Value communication protocol will be utilized at a practical level to establish a hierarchical infrastructure of data processing nodes. VC will process this raw data to determine the distribution network condition. In this endeavor, a new efficient way to monitor and maintain power networks will be examined. The suggested method will predict the existing and future status of the system, including upcoming breakdowns. At the top of the structure, aggregated information will be displayed to human grid operators to help them schedule maintenance or plan emergency actions. Real grid pilots and laboratory experiments in Finland will provide the required data to develop and train the suggested approach to predict intermittent earth faults.

INDEX TERMS *Condition monitoring, high impedance fault, intermittent earth fault, medium-voltage distribution network, voting classification.*

INTRODUCTION

Fault incidence is one of the most significant occurrences in the electric power system, which can have an impact on the system average interruption duration index (SAIDI) and the electricity supply quality. This occurrence will affect the power quality of customers, resulting in customer discontentment. [1, 2]. In essence, an intermittent fault maybe followed by a persistent fault. Therefore, to enhance the quality of the energy supply in MV distribution networks, condition monitoring (CM) and predictive maintenance (PM) in medium-voltage (MV) grids are necessary. Distribution system operators (DSOs) will be given the chance by CM to schedule maintenance to minimize system outages [3]. Detection of intermittent faults will aid DSOs in scheduling maintenance to avoid evolving such faults into a permanent one. For permanent (continuous) single-phase to ground faults, a number of fault location techniques that come under the fault passage indication (FPI) or distance estimation categories have been developed or are now in use. A variety of methods are available, such as impedance-based, traveling wave-based, and injection-based methods [1-5].

As for intermittent fault, reference [4] has thoroughly reviewed the merits and demerits of earth fault and intermittent fault indication and location methods in non-effectively grounded networks, including both centralized methods namely impedance, artificial intelligence, and traveling wave-based and decentralized ones, such as signaling, Fault Passage Indication (FPI), and relay-based methods. Researchers also have looked into accurate fault detection techniques [5]. The performance of the major signal-processing approaches, including Fourier Transform, Wavelet Transform, Stockwell Transform, and Mathematical Morphology, is evaluated in this article, along with a critical analysis of high impedance fault (HIF) detection. In [6,7] Altonen and Wahlroos proposed a universal earth fault detection method (independent of the fault resistance and the level of compensation) known as multi-frequency admittance-based earth fault detection, with which both restriking (intermittent) and earth faults can be detected. In [8,9] Druml et al. also shed some light on intermittent fault in medium voltage systems by conducting field experiments. Results of this study can help grid operators, especially in rural areas that reliable information about earth fault direction is of paramount importance. Regarding HIF, numerous studies have been undertaken over the years, and in the presence of HIF it has been empirically proven that the nonlinearity in fault impedance generates randomization in the voltage and current waveform [10-13]. Although there are many different HIF detection technologies available, it is difficult to make general conclusions about them because they are each analyzed using different HIF models and have different distribution systems and validation protocols. Significant technical challenges exist in the identification of LV and MV faults, and current faultfinding techniques are unable to detect and locate all sorts of LV and MV system's faults. Despite extensive research and numerous approaches that have been conducted and proposed to overcome this difficulty for intermittent fault detection in MV grids, it remains a challenge for power system engineers.

Due to the development of artificial intelligent techniques over the past decade, now it is frequently utilized for condition monitoring and preventative maintenance. These techniques are able to forecast emergent fault problems in MV-distribution networks and to design tools to automate the condition monitoring of power system assets.

Therefore, in this paper, we proposed a novel framework for intermittent earth fault detection based on real grid pilots and laboratory experiments. This framework uses a voting classifier constructed from four classifiers. The voting strategy of the classifier is the majority rule which has the potential to provide better flexibility in the system design. In order to prove our findings and the performance of the suggested framework, the main classifier results will be compared with other classifiers using multiple metrics.

VOTING CLASSIFICATIONS

Let us get more flexibility in designing the system by lowering the unison criterion. At least K classifiers must concur on the classification of a pattern to be accepted [14]. Additionally, we presumptively believe that the classifiers are autonomous and [$K > (H - 1)/2$] is a solid majority. In the event of incorrect classification, the output classes are maximum, dispersed with equal performance D = $Q\ (Correct_i),\ i = 1...H,\ V = 1\ D$] (refer to the preceding section).

In this particular scenario, a *signal* term is used to construct Q (accept), the probability that the quantity of relevant answers will be greater than or equal to M, and a *noise* term, the probability that there are at least K equal and incorrect classifications exists [14].

$$1 - G = Q(Accept)$$
$$= \sum_{i=K}^{H} \binom{H}{i} (D^i V^{H-i}) + \sum_{i=K}^{H} \binom{H}{i} (V^i D^{H-i} D^{H-i})$$
$$\times Q(\text{Equal response} \geq K \mid V^i D^{H-i})$$
$$= \sum_{i=K}^{H} \binom{H}{i} (D^i V^{H-i}) + \sum_{i=K}^{H} \binom{H}{i} (V^i D^{H-i})$$
$$\times \sum_{k=K}^{i} \binom{i}{K} \left(\frac{1}{(D-1)^{k-1}} \left(\frac{D-2}{D-1}\right)^{i-k}\right) \quad (1)$$

It is possible to derive the conditional probability of an accurate recognition Q (Correct | Accept) = Q (Correct, Accept)/ Q(Accept) by noting that Q (Correct, Accept) represents the probability that the acceptance takes place as a result of at least K equal and the signal phrase derived above is correctly classified.

$$\beta = \frac{Q(Correct, Accept)}{Q(Accept)} = \frac{Signal}{signal + noise} \quad (2)$$

There are multiple ways to approximate the above formulas. It is only possible to maintain a first-order approximation in 1 / Q if the number of classes is very big.

By considering the number Q of classes move toward infinity, K is equivalent to *H/2* (*H* even), and that β is nearly 1, by retaining only the dominating term, equation (1) can be approximated and calculating the factorial with Stirling's approximation:

$$1 - G \approx \binom{H}{K} (1 - D)^{H-K} D^K \approx 2^N [D(1 - D)]^{H/2} \quad (3)$$

In [15], more approximations are described. If positive relationships exist in the various networks, the aforementioned findings must be adjusted. For instance, the rejection rate in the limit of many nets needs to be different from zero to achieve an accuracy near 1 if the genuine probability distributions Q (pattern | class) are overlapping at the decision borders. The framework of the proposed methodology for intermittent fault detection is illustrated in Fig.1.

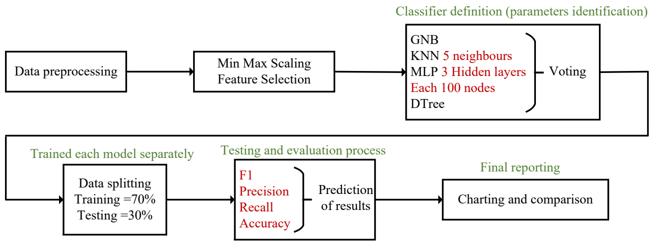

Fig. 1: The proposed flowchart for the intermittent fault detection methodology

CASE STUDY AND TEST SYSTEM

Fig. 2 shows the single line diagram of the test system. Different position of the simulated test system is selected for studying the effect of intermittent earth fault. Multiple run component used to run the simulation of intermittent earth fault and the following variables changed accordingly in this simulation: As well as intermittent fault with a wide range of resistance, fault resistance (earth fault which is also required for training purpose) is selected to be equal to 0 Ω, 100 Ω and 200 Ω. Fault duration is chosen to be 0.1 s, 0.2 s, and 0.3 s. Cable length is also considered as 'short', 'medium' and 'long'. The fault starting time is also considered to be variable, with the step of 2ms starting from 0.1 as shown in table 1. Fault place is another variable, which can be changed in this study. It should be noted that the sampling rate of the data is 4 kHz.

A measurement device is installed right after the transformer at the beginning of the feeders to monitor voltages and currents. In this study the phase a, b, c voltages, phase a, b, c currents of feeder 1, zero sequence of voltage, zero sequence of current, zero sequence angle of current, zero sequence magnitude of current, RMS value of fault current and fault current are captured and saved in Comtrade format to be used as input in the proposed method.

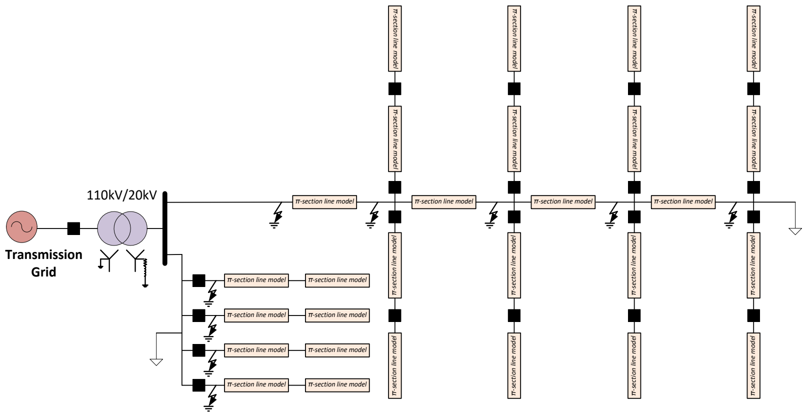

Fig. 2. Single line diagram of test system model

TABLE 1
Different setting during simulation

Run	00001	00002	00003	00004	00005	00006	00007	00008	00009	00010	00011	00012	00013	00014	00015	00016	00017	00018	00019	00020	00021	00022	00023	00024	00025	00026	00027
Fault starting time	0.1																										
Cable length	Short									medium									long								
Fault duration (s)	0.1			0.2			0.3			0.1			0.2			0.3			0.1			0.2			0.3		
Fault resistance (Ω)	0	100	200	0	100	200	0	100	200	0	100	200	0	100	200	0	100	200	0	100	200	0	100	200	0	100	200

RESULT AND DISCUSSION

In this study, the whole process was implemented using python language and scikit-learn library. The training and testing process was executed on an Intel Xeon E3 2697 CPU. The training time for the Voting classifier was 56 minutes. We split each dataset into a train and test set which is a subdivision of simulation results with desired parameters.

The rate of the split was 70 % and 30% for the train and test, respectively. Then, we combined all train and test datasets into each other, in order to have a single train and test dataset. In the next step, we shuffled each dataset to prevent any locality in the mentioned data for training and test purposes. With this method, we can be sure that each train and test dataset contains records with different parameters. All parameter settings of the applied methods are summarized in Table 2.

Table 2
Parameter tuning of investigated methods

Applied methods	Parameters setting
K-Neighbors	K=5
MLP	Three hidden layers with 100 nodes
Decision Tree	Criterion: Gini
Voting	Majority rule

In order to analyze the result of the proposed method, we have performed multiple evaluation techniques, including precision, recall, accuracy, and f1, which can be seen in Fig. 3 until Fig. 6.

Precision is defined as the measure for the evaluation of correctness in the results. As can be found from Fig. 3, the voting, KNN, and MLP have achieved better results, which means these methods were accurate in their classification task. Besides, VC has achieved the best precision among others. In other words, it is accurate in their targets. In Recall which is shown in Fig. 4, Voting has achieved the best result, meaning that the coverage of targets was wider than other methods. Also, gaussian naïve Bayes has a very close value to the voting classifier. These methods can cover more targets than the others. Simply the correctness and evaluation of correct classification have been done by the accuracy score based on Fig. 5. The voting classifier has achieved the best accuracy score and simply the most correct results, and accurate results overall belong to the voting classifier. The f1 measure is a method that combines precision and recall. It is a very popular metric for classification tasks.

The f1 score is the best way and also the most reliable way to compare the performance of multiple classifiers. The voting classifier achieved the best f1 score here, and it is shown that the voting classifier can perform the classification task better than the other classifiers which can be seen in Fig. 6.

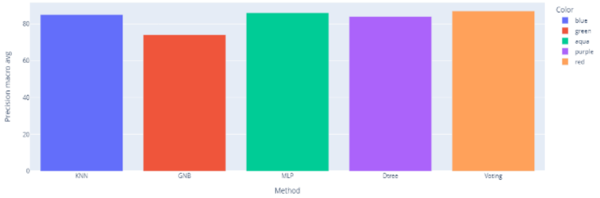

Fig. 3: Comparative precision values of applied methods

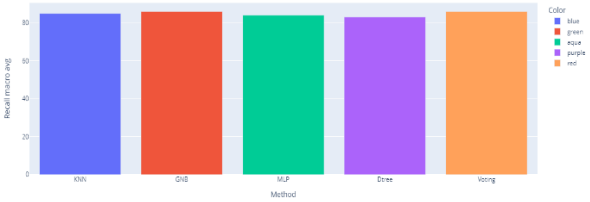

Fig. 4: Comparative recall values of applied methods

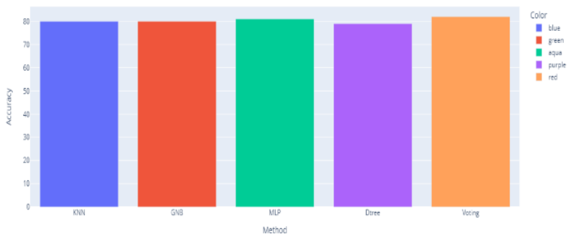

Fig. 5: Comparative accuracy values of applied methods

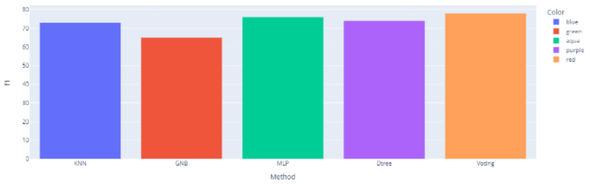

Fig. 6: Comparative f1 values of applied methods

The numerical results have been computed in detail for various metrics in Table 3.

TABLE 3
THE METRICS VALUES OF VARIOUS METHODS

Method	Precision macro avg	Recall macro avg	F1	Accuracy
KNN	0.85	0.85	0.73	0.8
GNB	0.74	0.86	0.65	0.8
MLP	0.86	0.84	0.76	0.81
Dtree	0.84	0.83	0.74	0.79
Voting	0.87	0.86	0.78	0.82

Overall, the voting classifier has achieved the best results in all metrics, which shows that the voting classifier can cover the data more than all other methods, it can also accurately classify them and it is also a stable and accurate method for the fault detection problem. Fig. 7 depicts the performance of different methods simultaneously.

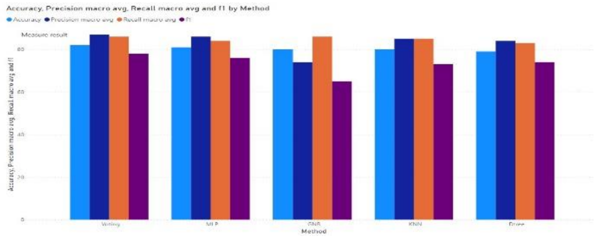

Fig. 7: Comparative values of all metrics of applied methods

CONCLUSION

This research proposed an intermittent earth fault detection approach for monitoring the condition of MV distribution networks based on the voting classification methodology. This collection of work examines a prospective new strategy that might improve the effectiveness of monitoring and maintaining electrical networks. Comparison between the results, based on various criteria such as Precision, Recall, F1, and Accuracy of VC technique and that of KNN, GNB, MLP, and Dtree shows the effectiveness of the VC method in the prediction of the existing and future faults of the system. This is why aggregated information displayed to human grid operators can help them schedule maintenance to avoid evolving intermittent faults into permanent ones.

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