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An Anomaly-based Technique for Fault Detection in Power System Networks

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***Abstract*— In recent years, fault detection in electrical power systems has attracted substantial attention from both research communities and industry. Although many fault detection methods and their modifications have been developed during the past decade, it remained very challenging in real applications. Moreover, one of the most important parts of designing a fault detection system is reliable data for training and testing which is rare. Accordingly, this paper proposes an anomaly-based technique for fault detection in electrical power systems. Furthermore, a One-Class Support Vector Machine (SVM) model and a Principal Component Analysis (PCA)-based model are utilized to accomplish the desired task. The used models are trained and tested on VSB (Technical University of Ostrava) Power Line Fault Detection dataset which is a large amount of real-time waveform data recorded by their meter on Kaggle. Finally, performance and Receiver Operating Characteristic (ROC) curves analyses of our results are exploited to verify the effectiveness of the proposed technique in the fault detection problem.**

Keywords- Fault Detection, Anomaly Detection, Power Networks, Support Vector Machine, Principal Component Analysis.

I. INTRODUCTION

Nowadays, the electrical power grids are growing in both size and complexity in terms of all sectors. One of the most serious problems in electrical power transmission and distribution is occurrence of electrical faults. An electrical fault is an abnormal deviation of currents and voltages from their normal states. In other words, electrical power lines carry normal values of currents and voltages during safe operation of the electrical system, but when a fault happens, excessively high voltages and currents flow across power lines which causes damage to devices and equipments [1][2].

The causes of electrical faults vary from equipment failures to environmental conditions or human errors. These faults are very harmful since they reduce the reliability of the electrical grid as well as cause huge economic losses. Furthermore, the consequences of occurrence of such faults are not only devices damage, but also service interruption and death of humans and animals. Therefore, early and effective electrical fault detection is a very necessary process to overcome this problem and to increase the satisfactory of customers [3][4][5].

Anomaly detection (also known as outlier detection) is a process in data mining that determines samples or events in a dataset that localize far away from normal behavior [6][7]. These anomalous samples can refer to a noise or potential opportunities [8]. Basically, anomalies are rare by definition and it is very difficult to gather a representative amount of them for modeling. For instance, fault detection problem is where we have a lot of ”normal” signals and not many samples of anomalies (faults) which we seek to detect. Hence, anomaly detection is the most suitable technique to detect "faulty" samples that deviating significantly from the "normal" cases [9][10]. Machine learning algorithms are extensively used to perform anomaly detection task due to their proved ability to learn from data [11].

The aims of this study are two-fold, as follows.

- Rather than using binary classification methods, an anomaly-based fault detection technique is proposed to identify the few faulty signals from the immense normal signals in power networks.
- Two anomaly-based detection methods are trained and tested over a real-time fault detection dataset which demonstrates the pattern of fault occurrence in real-world power networks.

The rest of this paper is organized as follows. Section II introduces the literature review of fault detection using shallow machine learning methods. The VSB dataset characteristics and feature extraction process are described in Section III. Then, Section IV shows the methodology of our experiments and a description of the used models. In Section V, a list of the used evaluation measures as well as a discussion of the experimental results are provided. Finally, conclusions are presented in Section VI.

II. LITERATURE REVIEW

In the open literature, dozens of studies have been published in the area of electrical power systems and their faults. A fault detection and classification on six phase transmission line were simulated using MATLAB and Simulink [12]. Then, they exploited an Artificial Neural Network (ANN) to protect six phase transmission line against ground faults. A Concurrent Fuzzy Logic (CFL) technique was applied in different simulated power transmission lines to predict faults and their locations [13]. In the study of [14], a simulated dataset of different faults in a high transmission line is used to train and test three SVM models to detect faults. Their method gave good results, especially, when using SVM with Gaussian Radial Basis kernel Function (RBF). Different ANNs have been introduced to detect faults of electric power transmission line using simulated data in MATLAB [15]. Fault detection and classification with satisfactory results on three phase electrical power transmission line using ANN on simulated dataset in MATLAB is introduced by Jamil et al. [16].

Singh et al. simulated three phase transmission line in MATLAB and used the data along with SVM classifier for fault detection and classification [17]. In the study of [18], an ANN classifier is applied on simulated data for fault detection and location in Extra High Voltage (EHV) transmission lines. A method using SVM to identify fault type, section and distance regarding the faulty phase is proposed in the study of [19]. Atul and Navita [20] presented an ANN approach for fault detection and classification in double circuits transmission line faults. They applied their ANN model on simulated data in MATLAB. In the study of [21], an ANN method is demonstrated to detect and classify faults in transmission line. Three classifier such like Generalized Regression Neural Network (GRNN), Probabilistic Neural Network (PNN), and An Adaptive Network Fuzzy Inference System (ANFIS) is used with simulated data in Simulink for fault detection, classification and location [22].

Ekici et al. used PNN model for classifying faults types and Resilient Propagation (RPROP) algorithm for detecting fault locations [23]. In the studies of [24][25], simulated data of Nigerian power system in MATLAB is used to train and test an ANN model for fault detection, classification and location. The study of [25] has got good results with accuracy is equal to 95.7%. An ANN architecture is presented for fault detection in a transmission line power system [26]. Koley et al. proposed a modular artificial neural network with hybrid wavelet transform for fault detection, classification and location. They performed their experiments on a single end data for six phase lines [27]. In the study of [28], a Back Propagation (BP) ANN architecture is presented as an alternative method for fault detection and classification.

It can be concluded that the previous studies in fault detection have the following two drawbacks: (i) Most of the previous studies utilized binary classification methods to detect electrical faults rather than anomaly-based detection, which the latter is the common case of fault detection because in real power networks, faults are rare. (ii) They used virtual datasets by simulating an electrical grid and recording volt and current values for each phase at fixed period of time which cannot model accurately the faults in real power networks. Therefore, to our knowledge, developing a anomaly-based detection technique for electrical fault detection is still a big challenge.

III. VSB DATASET

VSB dataset was firstly released in the VSB Power Line Fault Detection Kaggle Competition in 2018 [29]. The objective of this competition was to identify Partial Discharge (PD) events in electrical signals that are captured by a new device designed at the ENET Centre at VSB [30]. A PD is a localized and quick electric discharge that only partially bridges the insulation material between the conductors materials or electrodes. They are identified by localized higher than normal amplitude and high frequency spikes in the signal. Several types of PDs occur: internal, surface, corona or electrical treeing.

VSB is a modern power line fault detection dataset and publicly available on the internet [29]. The dataset consists of 8712 signal samples acquired from power lines of an electric grid which operates at 50 Hz. Each signal includes 800000 voltage measurements which are taken over 20 milliseconds (one grid cycle). Moreover, the underlying grid works on a 3-phase power scheme and all three phases are measured simultaneously. In addition to that, each signal has its target class, i.e., a label of "0" if the signal is "normal" or a label of "1", otherwise. Equally important that the number of "normal" samples in VSB dataset is 8187 (93.97%), whereas the "faulty" samples are only 525 (6.03%). This unbalancing between "normal" and "faulty" samples implies the importance of using anomaly-based detection with such an imbalanced dataset.

One of the emerging challenges of VSB dataset is the numerous number of features for each signal (800000) which makes it infeasible for shallow machine learning models, because such a high dimensional space of inputs will make the model to fail. Hence, a dimension reduction process is indispensably required. Accordingly, we performed a feature extraction process on each signal to obtain only 20 features out of 800000 voltage measurements of the signal. In order to accomplish this goal, we computed 19 of widely-used statistics that can describe the distribution and behavior of the data, whereas the 20th feature is the class label. The list of the 19 numeric features are as follows.

- Mean (also known as arithmetic mean or average) is the sum of a discrete set of numbers divided by the number of values.

$$Mean = \frac{\sum_{i=1}^{N} x_i}{N} \qquad (1)$$

  where x_i is the i^{th} voltage measurement of the signal and N is the number of voltage measurements which equals 800000.
- Standard deviation is a value that indicates the amount of variation of a set of numbers. As the value of standard deviation increases, the values of these numbers tend to spread away from the mean of the set.

$$Standard\ Deviation = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N}} \qquad (2)$$

where $\bar{x}$ is the mean of the voltage measurements.

- Maximum value of the voltage measurements.
- Minimum value of the voltage measurements.
- Percentile is a special type of quantile where a sample set is divided into 100 equal-sized intervals which enables the user to analyze the data in terms of percentages [31]. For example, the k^{th} percentile is the score below which $k\%$ of the samples are found. We computed five percentile values which are 1%, 25%, 50%, 75% and 99% percentiles. These percentiles can be computed by firstly ordering the voltage measurements of the signal in ascending order then taking the value from the ordered list which corresponds to that rank z.

$$z = \left\lceil \frac{P}{100} N \right\rceil \quad (3)$$

where P is the percentage value.

- Relative percentile, also known as spectra, is data deviation from the mean. We computed seven relative percentile values for each signal which are 0%, 1%, 25%, 50%, 75%, 99% and 100% relative percentiles. These values can be computed according to the following equation.

$$P^{th} Relative\ Percentile = P^{th}\ Percentile - Mean \quad (4)$$

It is worthy to say that 0% and 100% percentiles are equal to minimum and maximum values, respectively.

- Lower bound and Upper bound are the lower and upper bands of the voltage measurements. They can be calculated according to Equations (5) and (6), respectively.

$$Lower\ Bound = Mean - Standard\ Deviation \quad (5)$$

$$Upper\ Bound = Mean + Standard\ Deviation \quad (6)$$

- The height of the signal is the difference between the maximum and minimum values of the voltage measurements.

$$Height = Maximum - Minimum \quad (7)$$

Table I summarizes the main characteristics of the used dataset.

TABLE I. THE MAIN CHARACTERISTICS OF VSB DATASET.

Characteristic	VSB dataset
Year	2018
Number of classes	2
Number of features	20
Distribution of training set	Normal=7100 Faulty=0 Total=7100
Distribution of test set	Normal=1087 Faulty=525 Total=1612

IV. METHODOLOGY AND MODELS

We carried out two main empirical experiments, each of them on one of the anomaly detection models. In the next subsections, the experimental setup and a brief description of the used models are explained.

A. Methodology

Our methodology is designed to be obvious and straightforward. It consists of four sequential phases, namely, preprocessing, pre-training, training, and testing. To start with preprocessing phase where a tuple of 20 features is extracted from each signal data as explained in Section III. Afterwards, the extracted tuples are normalized into [0,1], except the "Class" feature, using the following Min-Max transformation formula:

$$x_i = \frac{x_i - Min}{Max - Min} \quad (8)$$

where x_i is the numeric feature of the i^{th} sample, Min and Max are the minimum and maximum values for every numeric feature, respectively. The last step in the preprocessing phase is creating the training and testing sets. Since the anomaly detection usually uses only the normal samples in the training process, we selected randomly 7100 (81.5%) normal samples in the training set. On the other hand, the remaining 1612 (18.5%) samples are selected in the test set which contains both normal (1087) and faulty (525) samples.

Then, the pre-training phase is taken place when a hold-out sampling method is used to split the training set into two separate parts with 6850 normal samples in the training-only data and 250 normal samples in the validation data. The validation set is also contaminated with 125 faulty samples randomly selected from the test set which raises the number of samples in the validation set to 375 samples. The main aim of using the training-only and validation sets in the pre-training phase is to find out the optimal hyperparameters of the models. After that, the pre-training phase determines the optimal hyperparameters of the particular anomaly-based detection model by performing a loop over a grid of predefined range. It tries all possible combinations of the model hyperparameter values and identify the best learners. For each settings of the model hyperparameters, the model is trained on training-only data and then validated over validation data. Then, it compares the accuracy values over all models to get the combination of settings which maximizes the accuracy.

Subsequently, in the training phase, we constructed the particular anomaly-based detection model and tuned it by the given optimal hyperparameters. The resulting model is trained on the full training set. Afterwards, in the testing phase, the trained model is tested on the test set.

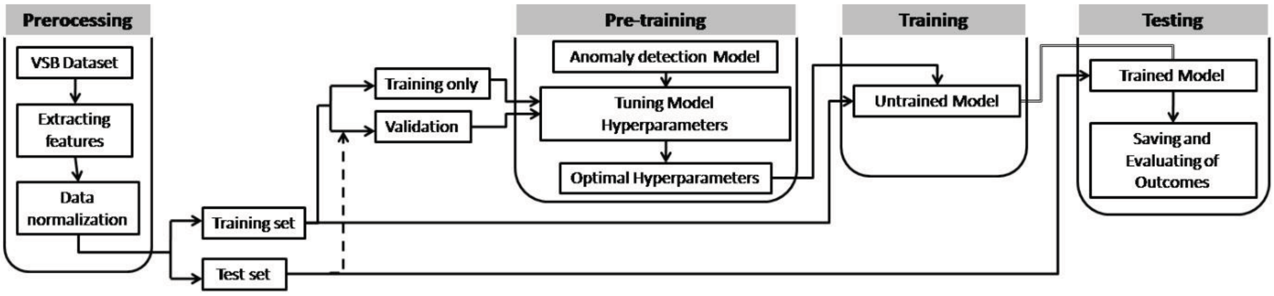

Figure 1. The methodology diagram of the experiments.

Finally, the evaluation metrics are calculated and stored for further processing later. Figure 1 depicts the diagram of our methodology. Table II presents the optimal hyperparameter values of the models after finishing of the pre-training phase.

TABLE II. THE HYPERPARAMETERS OF EACH MODEL AND THEIR RANGES AND SELECTED VALUES.

Model	Parameter	Range	Selected value
One-class SVM	Nu	[0.001,0.1] Step=0.01	0.1
	Epsilon	[0.001,0.1] Step=0.01	0.001
PCA	Rank	[2,10] Step=2	2
	Oversampling	[2,10] Step=2	4
	Center	{True, False}	False

B. Models

Azure Machine Learning (AML) studio [32] is exploited as an environment for executing our experiments. Further, two of AML's built-in anomaly-based detection models are utilized to detect electrical fault patterns over VSB dataset. The reason behind using AML is that it provides a free cloud-based machine learning platform which has many useful pros such as offering a web-based working platform with a collaborative and interactive design as well as it has a high computing capacity for long running experiment [33][34]. A brief description of one-class SVM and PCA-based anomaly detection models is given in the following subsections.

1) One-Class SVM: SVM is a widely-used model in supervised learning for regression or classification tasks. It can learn from training data and recognize patterns. Typically, the SVM model analyzes the samples of the training set and seeks to divide these samples into separate classes along with as wide a gap among them as possible. Then, the SVM model assigns unseen data to the class that has the minimum error value between the data point and its support vector [35].

Unfortunately, the aforementioned process of the SVM algorithm can work properly only with balanced datasets, that is, a dataset with a representative amount of samples for each class which does not exist in the electrical fault detection problem. Therefore, the one-class SVM model trains only on data that belongs to one class with majority samples. In the case of electrical fault detection, the one-class SVM model trains only on "normal" samples. Then, it learns the characteristics of the normal samples and builds a profile for them. Afterwards, it can predict whether a new sample is like the normal samples or not [35].

There are two main hyperparameters of one-class SVM model, namely, Nu (η) and Epsilon ($\mathcal{E}$). The Nu hyperparameter is a value that controls the gap between normal points and outliers. It corresponds to the nu-property introduced in the study of [36]. Moreover, the Epsilon hyperparameter is considered as a stopping criteria value. For each iteration, The one-class SVM model computes the stopping tolerance and compares it with the Epsilon parameter value. If the stopping tolerance is less than the Epsilon parameter value, the one-class SVM algorithm stops running or proceeds to next iteration, otherwise [35].

2) PCA: PCA is a common technique in machine learning for measuring variance in the data. It also can be used for feature reduction where the correlation among features is calculated and a minimized combination of features that significantly affects the classification or regression score is found. The PCA algorithm then exploits the features in the minimized combination to create a new compact feature space (principal components) [37].

The PCA-based anomaly detection model can resolve the electrical fault detection problem by learning from the training set what a combination of features that are well-suited for identifying normal samples. Then, it creates the principle components for these features. After that, it analyzes any unseen data by computing its projection on the new feature space, together with a normalized error. The PCA-based anomaly detection model uses the normalized error to detect faults with higher normalized error values.

There are three main hyperparameters of PCA-based anomaly detection model which are: Rank, Oversampling, and Center [37].

V. Results and Discussion

The features extraction process from VSB dataset is implemented using Python version 3.6.4 [38] along with NumPy library [39]. The used evaluation metrics and obtained results are explained below.

A. Evaluation Metrics

Since the test set has a mixture of "normal" and "faulty" instances, the test process of the models is deemed to be a binary classification task. Thus, there are four major outcomes can be gained from this task, namely, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Then, the four outcomes are utilized to calculate four well-known evaluation metrics in order to evaluate the performance of the used models in the anomaly-based fault detection problem. The list of the definition and corresponding equations of the used evaluation metrics are as follows:

- Accuracy is the rate of truly classified samples in the test set.

$$Accuraccy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

- Precision determines the classifiers exactness, that is, the rate of data points that are correctly labeled as "faulty" from all data points in the test set that were classified as "faulty".

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

- Recall determines the classifiers completeness, that is, the rate of data points that are truly classified as "faulty" for all "faulty" data points in the test set. It also known as Hit, Sensitivity, Detection Rate (DR) or True Positive Rate (TPR).

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

- F1-Score is a measure that combines both Precision (*P*) and Recall (*R*) metrics. It also called F1 metric.

$$F1\ Score = \frac{2PR}{P+R} \quad (12)$$

B. Performance Analysis

The effectiveness of a model in fault detection depends on its score of evaluation metrics. The higher accuracy, precision, recall, and F1-Score values, the more efficient the model is. Table III presents the outcome values for each model. Table IV shows the percentage values of the evaluation metrics for each model. Further, the bold values in Table III and IV represent the best results of the two models.

TABLE III. THE OUTCOME VALUES FOR EACH MODEL.

Outcome	Model	
	SVM	PCA
TN	**935**	897
TP	352	**381**
FN	173	**144**
FP	**152**	190

TABLE IV. THE PERCENTAGES OF THE EVALUATION METRICS FOR ALL MODELS.

Metric (%)	Model	
	SVM	PCA
Accuracy	**79.84**	79.28
Precision	**69.84**	66.73
Recall	67.05	**72.57**
F1-Score	68.42	**69.53**

Meanwhile the one-class SVM model detected more faulty samples than the PCA model, the PCA model identified more normal samples than the one-class SVM model. This due to the nature of the one-class SVM classifier which enables it to recognize the difference between the two classes. On the other hand, the PCA model links the features together in its new space and tends to identify the characteristics of the most occurrence samples (normal). In general, the results of the two models are deemed to be not very high because to potential existence of noise in the dataset. However, all the used models still have an acceptable performance. In order to interpret the results visually, Figure 2 shows a comparison between the gained evaluation metrics for all models.

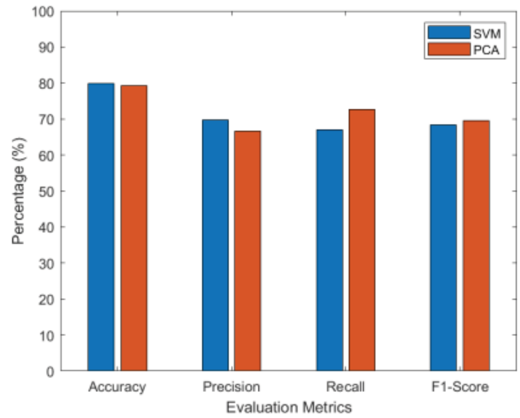

Figure 2. Comparison of standard metrics between models on VSB dataset.

Alternatively, the ROC curve is a plot of the recall against the false alarm rate of a classifier [40]. When the ROC curve of a classifier lies on the diagonal line, this means that the classifier reaches 50% of performance. On the other hand, the classifier achieves the ideal performance with 100% if and only if its ROC curve matches the top-left corner. Figure 3 depicts ROC curves of the used models on VSB dataset.

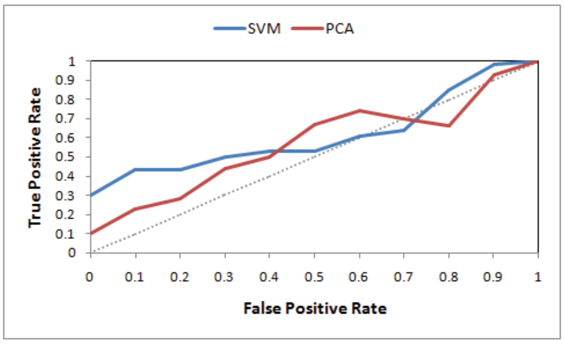

Figure 3. ROC curves of the used models over VSB dataset.

Furthermore, the Area Under the ROC Curve (AUC) is a numeric value to trade-off between different ROC curves [41][42]. The AUC value of an ROC curve is in [0,1]. Table V presents AUC values of ROC curves which are plotted in Figure 3.

TABLE V. AUC VALUES OF ROC CURVES.

Model	AUC
One-class SVM	**0.7359**
PCA	0.6864

VI. CONCLUSION

Fault detection is deemed to be the cornerstone of electrical power system reliability. It is not only increases the quality of the service, but also decreases the economic losses. The lack of real-time electrical fault detection dataset is considered to be an emerging challenge in the electrical fault detection area due to the high cost of collecting faulty samples which are rarely occurred. Hence, we proposed an anomaly-based electrical fault detection technique that builds a profile for the normal samples and then tries to find out any samples deviate from it. Furthermore, two anomaly-based detection models, namely, one-class SVM and PCA-based models are utilized to accomplish the desired goal. They are trained and tested over VSB dataset which is a real-time electrical fault detection dataset. The experimental results reveal that our technique has a good performance in fault detection with accuracy approached 80% for the two models.

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