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Araştırma Makalesi / Research Article

Power Transmission Line Fault Detection and Classification

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Abstract

It is very important to find short circuit faults of power transmission lines (PTL) quickly and efficiently. Most methods in the literature use classification algorithms for fault detection, but their use in real-time applications increases fault detection time. The reason for this that while the fault detection process is performed with the classification algorithm, the features of incoming data must be extracted continuously by using a window function. In this study, principal component analysis (PCA) or independent component analysis (ICA) algorithms that are suitable for real-time fault detection are proposed to decrease the fault detection time. Besides, time-domain statistical properties of the PTL signals computed over a period of time are proposed to increase classification speed and accuracy. The results show that PCA and ICA algorithms can detect all faults in real-time data streams, and the classification results are 100% for 10 faults with the proposed features.

Keywords: Fault detection, Feature Extraction, Independent Component Analysis, Principal Component Analysis, S Transform.

Güç İletim Hatlarında Hata Bulma ve Sınıflandırma

Öz

Elektrik iletim hatlarının (EİH) kısa devre arızalarını hızlı ve etkili bir şekilde tespit etmek çok önemlidir. Literatürdeki çoğu yöntem, arıza tespiti için sınıflandırma algoritmalarını kullanmaktadır, ancak bu yöntemlerin gerçek zamanlı uygulamalarda kullanımı, arıza tespit süresini artırmaktadır. Bunun nedeni, arıza tespit süreci sınıflandırma algoritması ile gerçekleştirilirken, gelen verilerin özelliklerinin sürekli olarak bir pencere fonksiyonu kullanılarak çıkarılması gerektiğidir. Bu çalışmada, arıza tespit süresini azaltmak için gerçek zamanlı arıza tespiti için uygun olan temel bileşen analizi (TBA) veya bağımsız bileşen analizi (BBA) algoritmaları önerilmektedir. Ayrıca, sınıflandırma hızını ve doğruluğunu artırmak için belirli bir zaman aralığında hesaplanan EİH sinyallerinin zaman alanı istatistiksel özellikleri önerilmektedir. Sonuçlar, TBA ve BBA algoritmalarının gerçek zamanlı veri akışlarında tüm arızaları tespit edebildiğini ve önerilen özellikler ile 10 arıza için sınıflandırma sonuçlarının %100 olduğunu göstermektedir.

Anahtar Kelimeler: Hata Bulma, Özellik Çıkarımı, Bağımsız Bileşen Analizi, Temel Bileşen Analizi, S Dönüşümü.

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1. Introduction

In the transmission lines, reasons for the short circuit fault could be a lightning strike, falling tree branches, fog, or other environmental factors. Fast detection and classification of these faults are very important to maintain power transmission and reduce the adverse impacts, especially a transmission line breaks down. Also, fast detection and rapid restoration of electricity reduce the outage time, and reducing the outage time increases the safety and reliability of the transmission line, and reduces system operating costs. When a fault occurs in a transmission line, the current of the faulty line changes, and this also affects the healthy line currents, so identifying the fault type is a complex task and needs extra effort. Also, the increasing complexity of modern PTL systems has greatly raised the importance of fault detection and classification studies. There are some works in the literature that attempt to employ classification algorithms to detect and classify these faults. These methods typically employ various classification algorithms during the fault detection and classification phases, such as Support Vector Machines (SVM) (Magagula, Hamam, Jordaan, & Yusuff, 2017; Moloi & Akumu, 2019), artificial neural networks (ANN) (Fernandes, Costa, & De Medeiros, 2016; Jamil, Sharma, & Singh, 2015; Malla, Coburn, Keegan, & Yu, 2019; Silva, Souza, & Brito, 2006), and k nearest neighbors (k-NN) (Asadi Majd, Samet, & Ghanbari, 2017) algorithms. While (Adhikari, Sinha, & Dorendrajit, 2016; Guillen, Idarraga-Ospina, Zamora, Paternina, & Ramirez, 2014; Kasinathan & Kumarappan, 2008) utilize the same algorithm for both the fault detection and classification phases, methods employing two different algorithms connect them in a cascade form, with one algorithm dedicated to detection and the other to classification. Once a fault is detected by the first algorithm, the second algorithm is employed to identify the fault types(Silva et al., 2006; Singh, Panigrahi, & Maheshwari, 2011) .

Most studies use Fourier transform (FT), short-time Fourier transform (STFT), or wavelet transform (WT) as feature extraction methods to determine the fault characteristics for classification algorithms (Bhowmik, Purkait, & Bhattacharya, 2009; Samantaray & Dash, 2008). There are some shortcomings in these methods, so the feature extraction method is preferred depending on the application. Since FT does not have time information, STFT, which utilizes equal time windows, could be preferred. It is also possible to benefit from the time information of the signal by using WT which uses a different window function for analyzing different frequency bands. Even though WT is highly suited for feature extraction (Yumurtaci, Gǒkmen, Kocaman, Ergin, & Kiliç, 2016), it needs some improvements to classify faults (Pyare Lal Tandan & Abhijit Mandal, 2015). To overcome these difficulties, S-transform (ST), an extension to the Gabor Transform and WT, is utilized in some works (Roy & Bhattacharya, 2015; Samantaray, 2013). The most significant characteristic of the Short-Time Fourier Transform (STFT) is its complete convertibility between the time domain and the frequency domain, both forward and inverse. However, the computation of the STFT requires more time compared to the Wavelet Transform (WT).

In addition, classification algorithms, used in real-time fault detection, need to use the windowing system for feature extraction (Asadi Majd et al., 2017; Fernandes et al., 2016; Guillen et al., 2014; Jamil et al., 2015; Kasinathan & Kumarappan, 2008; Magagula et al., 2017; Malla et al., 2019; Moloi & Akumu, 2019; Silva et al., 2006), as seen in Figure 1. In these systems, features are extracted with a sliding window technique, as long as the data is received. Due to the large amount of incoming data, it is very difficult to derive features with a sliding window, especially if the data transformation is included (Malla et al., 2019). This is the main disadvantage of the classification algorithms, used in the fault detection phase, and makes it difficult to implement as a real-time fault detection application.

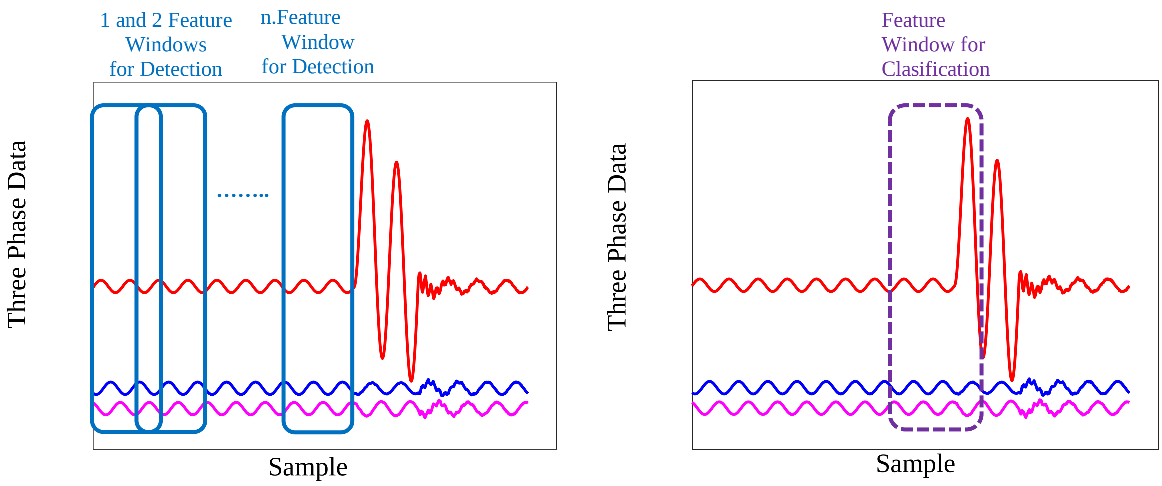

Figure 1. Fault detection and classification phases of conventional algorithms

In this paper, the PCA or ICA algorithm, appropriate real-time fault detection methods, is suggested to detect faults. The first important feature that makes them possible candidates for real-time fault detection is to process the received data one by one. The second one is that they only need faultless data to detect faults. One by one fault detection processes of these algorithms is shown in Figure 2. As can be clearly seen from Figure 2, the processing loads of the PCA and ICA algorithms are not high, and their applicability is simpler than the classification algorithms for the fault detection. Once a fault is detected, the feature extraction window, as illustrated in Figure 2, is utilized a single time to determine the fault type within classification algorithms.

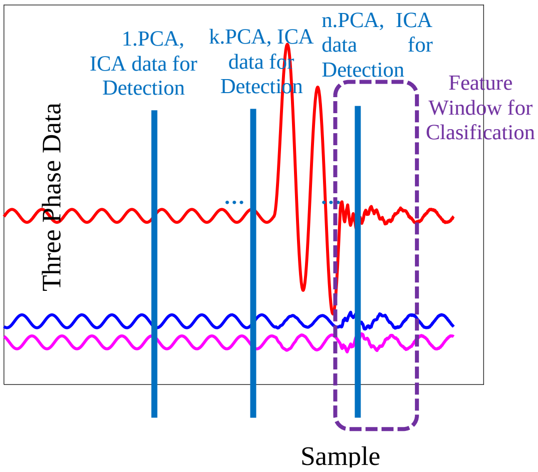

Figure 2. Fault detection phase of PCA and ICA algorithms and classification phase of classification algorithm

2. Fault Detection

2.1. PCA based fault detection method

PCA is an unsupervised technique that has been utilized in several industrial processes by MacGregor et al (MacGregor, Kourti, & Nomikos, 1996), and has appeared in a wide variety of process monitoring articles. The mixing model considered for PCA and ICA is linear

$$X = AS \tag{1}$$

where $S = [s_1, .., s_m]^T$ is unknown source vector, X is source signal mixtures (observed signals) via unknown mixing matrix A . The purpose of PCA is to estimate the inverse of mixing matrix A^{-1} by using the assumption of *uncorrelatedness* of the source signals. It transforms a set of observations of potentially correlated variables into a set of values of linearly uncorrelated variables known as principal components (Li et al., 2018).

In fault detection applications, PCA algorithm decomposes data matrix X into principal component subspace and residual subspace as follows:

$$X = TP^T + E = \sum_{i=1}^{a} t_i p_i^T + E \tag{2}$$

where $X \in R^{nxm}$ is data matrix with n (the number of observation) rows and m (measured variables) columns, $T \in R^{nxa}$ is score matrix which contains information about relationships between observations, $P \in R^{mxa}$ is loading matrix which has information about relationship between variables, $E \in R^{nxm}$ is residual matrix, and superscript T means transposition of the matrix. An important part of equation (2) is the $(a \leq m)$, which is the number of principal components and determined by different techniques (Chatfield & Collins, 2018; SW, Afifi, & Clark, 1997). To find the principal component and the residual subspace, first, the covariance matrix of the data matrix (R_x) is calculated as follows

$$R_x = E\{XX^T\} \tag{3}$$

Then, using Eigen-decomposition of $R_x = PDP^T$, the loading matrix P can be found as eigenvectors of R_x, and the score matrix can be expressed as

$$T = P^T X \tag{4}$$

Once the loading and score matrixes have been calculated, the residuals can be calculated in the following fashion,

$$E = X - \hat{X} = X - TP^T \tag{5}$$

To monitor system and detect fault, Hotteling's T^2statistics and second statistics SPE are used in PCA based methods. T^2 statistics at sample *k* can be calculated as

$$T^2(k) = x(k)^T PD^{-1} P^T x(k) \tag{6}$$

where $T^2(k)$ is the *k*th sample vector of T^2, $x(k)$ is the *k*th sample vector in X . If the *X* data are from a multivariate normal distribution, *F* distribution can be used to obtain the upper confidence limit for T^2 (threshold for T^2) as follows,

$$T^2_{a,n,\alpha} = \frac{a(n-1)}{n-a} F_{a,n-a,\alpha} \tag{7}$$

where *n* represents the number of samples in the dataset, *a* denotes the number of the principal components, and α signifies the level of significance.

Squared prediction error (SPE) statistic, associated with noise, does not suffer from inaccuracies in the smaller eigenvalues and is calculated as

$$SPE(k) = e(k)^T e(k) = x(k)^T (I - PP^T) x(k) \tag{8}$$

where $e(k)$ is the kth observation vector of E, I is identity matrix. Calculation for the upper confidence limit of the *SPE* (threshold for *SPE*) depends on its approximate distribution (Bakdi & Kouadri, 2017)

$$SPE_\alpha = \theta_1 \left(\frac{h_o c_\alpha \sqrt{2\theta_2}}{\theta_1} + 1 + \frac{\theta_2 h_o (h_o - 1)}{{\theta_1}^2} \right)^{\frac{1}{h_o}} \tag{9}$$

with

$$\theta_i = \sum_{j=a+1}^{m} \lambda_j^i \tag{10}$$

$$h_o = 1 - \frac{2\theta_1 \theta_3}{3{\theta_2}^2} \tag{11}$$

where c_α is the confidence interval and taken from standard tables of the error function.

Block diagram of PCA algorithm for fault detection can be seen in detail in Figure 3. First, the block of the PCA model is applied only one time to calculate the threshold values. In this block, only faultless current signals are used in the PCA as the training signals. The thresholds are calculated from the principal components using the confidence limit finding methods. Then, the current values of the tested system are processed one by one by using (6) and (8) to calculate T^2, SPE statistics. If there is a fault in the system, these calculated statistics must be bigger than the thresholds calculated in PCA model. Upon fault detection, the fault classification phase commences, as illustrated in the block diagram in Figure 3. In this phase, the features are extracted only once and classified using classifiers.

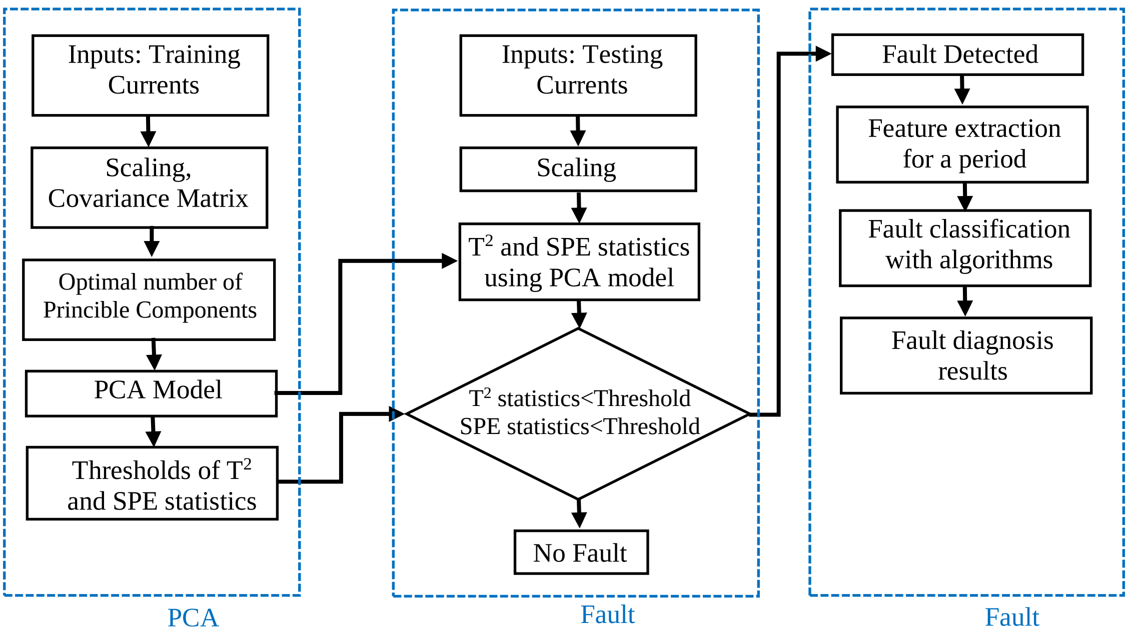

Figure 3. The block diagram of PCA for fault detection and classification.

2.2. FastICA fault detection method

The main difference between PCA and ICA is that ICA uses higher-order statistics to decompose mixed signals into a set of independent signals, whereas PCA uses second-order statistics. Also, PCA can be used as preprocessing step in some ICA algorithm. Among ICA algorithms that follow a linear combination of variables, the FastICA algorithm is the most popular and fastest algorithm. The FastICA algorithm utilizes kurtosis, negentropy, or maximum likelihood method to measure statistical independence. In this paper, negentropy based FastICA algorithm is used, and its cost function is defined as follows

$$J(y) = [E\{G(y)\} - E\{G(v)\}]^2 \tag{12}$$

where $J(y)$ is the non-Gaussian measurement function, v is a Gaussian variable, G is a non-quadratic function, and y can be computed using $y = D^{-1/2}P^T X$, where D is diagonal eigenvalue matrix of R_x. The process of decomposition of signals is accomplished by optimization of equation (12) and constituted as follows (Hyvarinen, 1999)

1. Define a random initial vector w and normalize it to unity.
2. Set $w \leftarrow E\{yg(w^T y)\} - E\{\acute{g}(w^T y)\}w$, where $g, \acute{g}$ are the first and second-order derivatives of G, respectively.
3. Normalize $w \leftarrow {w}/{\|w\|}$.
4. If not converged, return to step 2. Otherwise, calculate one independent component $y = wx$.

The function G could be any non-quadratic function, and three most used nonlinear functions are seen as follows,

$$G_1(y) = \frac{1}{a_1} \log\cosh(a_1 y) \tag{13}$$

$$G_2(y) = \exp\left({-a_2 y^2}/{2}\right) \tag{14}$$

$$G_3(y) = y^4 \tag{15}$$

where $1 \leq a_1 \leq 2$ and $a_2 \approx 1$. G_1 was used as nonlinear function in this work.

Three types of monitoring statistics are utilized to calculate the confidence limit in the fault detection studies of the ICA algorithms: I^2 statistics for the systematic part of the data, SPE statistics for the non-symmetric part of the data, and I_e^2 statistics for the excluded part of the data. The three statistics at sample k are defined as follows,

$$I^2(k) = x(k)^T W_d^T W_d x(k) \tag{16}$$

$$I_e^2(k) = x(k)^T W_e^T W_e x(k) \tag{17}$$

$$SPE(k) = e(k)^T e(k) = (x(k) - \hat{x}(k)^T)^T (x(k) - \hat{x}(k)^T) = \left(W_e x(k)\right)^T \left(W_e x(k)\right) \tag{18}$$

where W_d is the dominant part, W_e is the remaining rows of the matrix W. The confidence limits of the three statistics (thresholds) can be calculated by kernel density estimation (KDE) method (Martin & Morris, 1996; Silverman, 1986). The confidence limit of the data is point occupying 99% of area under the KDE function. A kernel density estimator is defined as follows

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K \left\{ \frac{x - x_i}{h} \right\} \tag{19}$$

where x is the sample point for KDE, x_i is a sample data from the measured signal, h is the bandwidth, n is the number of measurement signals, and K is the nonlinear kernel function. While the specific type of kernel K is not of critical importance, this study employed the Gaussian kernel function, which is the most commonly utilized kernel function (Silverman, 1986). Block diagram of ICA for fault detection can be seen in Figure 4. As can be seen in the block diagram, all stages of PCA and ICA algorithms are similar.

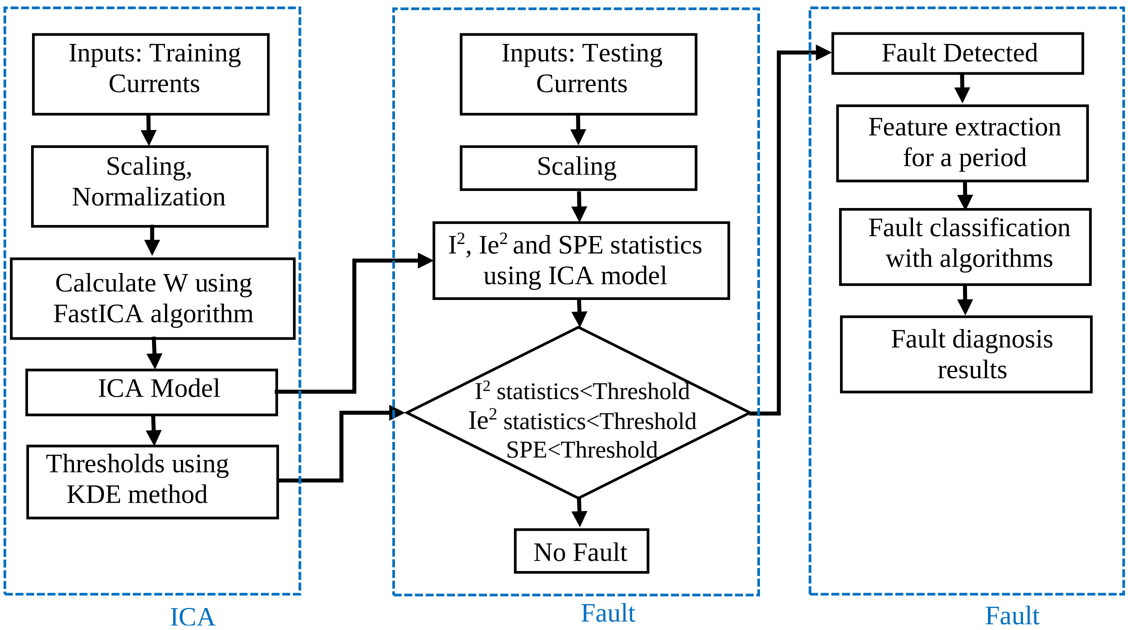

Figure 4. The block diagram of ICA for fault detection and classification.

3. Fault Classification

This section introduces feature extraction methods used in classification studies. The flow chart of fault classification is as shown in Figure 3 and 4. Four classification algorithms, including Support

Vector Machine (SVM), Artificial Neural Network (ANN), Decision Trees (DT), and K-Nearest Neighbors (KNN) were used as classification algorithms to identify fault types.

3.1. Feature Extraction

In the literature, a number of feature extraction methods have been employed to deal with fault detection in power transmission line (Godse & Bhat, 2020; Kumar et al., 2018; Yumurtaci et al., 2016; Yusuff, Jimoh, & Munda, 2011) . It is expected from the feature extraction method that they extract features quickly and have high classification results. For feature extraction, (Abd Allah, 2014; Thirumala, Kanjolia, Jain, & Umarikar, 2020) used post-fault samples for a half cycle period. But the features of the faultless phases for the half-cycle period will change according to the inception position of the feature extraction. This can increase the number of training samples required per class. As a solution of this problem, it is proposed to extract features from one cycle in this work. The main advantage of this is that these features never change for faultless phases and are almost zero for the mean value. Therefore, mean value, variance and kurtosis of the one cycle signals were used to reduce the feature extraction time and the number of the training samples. To observe the classification performance of the features for one cycle signals, Wavelet transform (WT) and S-Transform (ST) based features were also extracted and the classification performances were compared.

3.1.1. Feature Extraction using ST

The Stockwell Transform (ST) extends the Wavelet Transform (WT) by utilizing the Morlet wavelet as its fundamental wavelet. A notable advantage of ST is that the Gaussian window is adaptable over time, a property not shared by traditional wavelets (Pinnegar & Mansinha, 2003). ST transform of x(t) signal is given as

$$s(t,f) = \int_{-\infty}^{\infty} x(t) w(t-\tau, f) e^{-2\pi i f \tau} d\tau \tag{20}$$

where $w(t-\tau, f)$ is called the window function and can be expanded to form ST as follows

$$s(t,f) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sigma(f)\sqrt{2\pi}} e^{((t-\tau)^2)/(2\sigma f^2)} e^{-2\pi i f \tau} d\tau \tag{21}$$

where τ regulates the temporal position of the Gaussian window, $\sigma(f)$ represents the standard deviation of the Gaussian window, calculated as follows

$$\sigma(f) = \frac{1}{|f|} \tag{22}$$

When the standard deviation of the Gaussian window is modified as follows, the performance of ST in terms of time-frequency contours can be improved.

$$\sigma(f) = \frac{1}{a + {}^{b}\!/\!\sqrt{f}} \tag{23}$$

where the values of a and b range between 0 and 1. Using the new $\sigma(f)$ Gaussian window can be expressed as follows

$$w(t,f) = \frac{a + b\sqrt{f}}{k\sqrt{2\pi}} e^{\left((a+b\sqrt{f})^2 t^2\right)/(2k^2)} \tag{24}$$

where $k < \sqrt{a^2 + b^2}$. ST can now be formulated as follows

$$s(t,f) = \int_{-\infty}^{\infty} x(\alpha + f) e^{(-2\pi^2\alpha^2k^2)/\left(a+b\sqrt{|f|}\right)^2} e^{2\pi i\alpha\tau} d\alpha \tag{25}$$

ST transform, as defined in equation (25), is applied to single cycle of post-fault current signals following fault detection. The standard deviation, energies, entropies, kurtosis values of the ST signals are utilized as features and computed as follows

$$Mean(s) = \frac{1}{n+j} \sum abs\big(s(j,n)\big) \tag{26}$$

$$St.Deviation = \sqrt{\frac{1}{n+j} \sum \big(abs\big(s(j,n)\big) - Mean(s)\big)^2} \tag{27}$$

$$Energy = \sum \Big(abs\big(s(j,n)\big)\Big)^2 \tag{28}$$

$$Entropy = \sum -P\big(s(j,n)\big) log\Big(P\big(s(j,n)\big)\Big) \tag{29}$$

$$Kurtosis = \frac{\frac{1}{n+j}\Sigma\big(abs\big(s(j,n)\big) - Mean(s)\big)^4}{\left(\frac{1}{n+j}\Sigma\big(abs\big(s(j,n)\big) - Mean(s)\big)^2\right)^2} \tag{30}$$

3.1.2. Feature Extraction using Mean,Variance and Kurtosis Values

The mean value of a signal is a well-known and widely used statistical technique for feature extraction (Abd Allah, 2014). The reason for choosing the mean value of one cycle signal as a feature in this study is that the mean value of the periodic and symmetric signal is zero for one cycle. It can be clearly seen from Figure 5.a that when the mean value of one cycle signal is used, the starting point of the mean value calculation is not important. The important thing is to calculate the mean value of a signal for one period after the starting point, and the result is zero ($M_1=M_2=M_3=0$). As shown in Figure 5.b, if the symmetry of a signal is distorted by a fault, the mean value of the affected region will be different from zero ($F_1 \neq 0$, $F_2=F_3=0$). Also, it can be said that the mean value calculation for half or quarter cycle is different than zero, and depends on the starting point of the calculation.

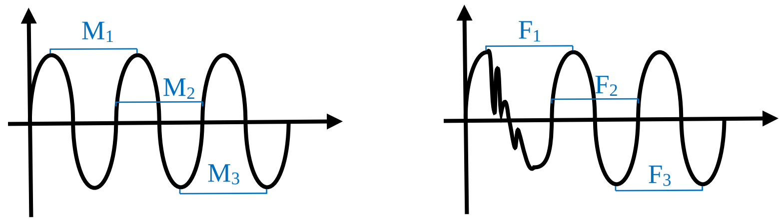

Figure 5. Definition of periods for a) faultless signal and b) faulty signal

The mean value of a periodic signal can be defined as follows

$$M_i = \frac{1}{T}\int_{n}^{n+T} I(t)dt \tag{31}$$

where *T* is period. The number of samples per cycle is calculated as follows

$$Samples = \frac{f_s}{f_l} \tag{32}$$

where f_s is sampling frequency and f_l is line frequency. The variance and kurtosis values of a periodic signal can be defined as follows

$$V_i = \frac{1}{T}\int_{n}^{n+T} (I(t) - M_i)^2 dt \tag{33}$$

$$K_i = \frac{\frac{1}{T}\int_{n}^{n+T}(I(t) - M_i)^4 dt}{\left(\frac{1}{T}\int_{n}^{n+T}(I(t) - M_i)^2 dt\right)^2} \tag{34}$$

4. Simulation and Discussions

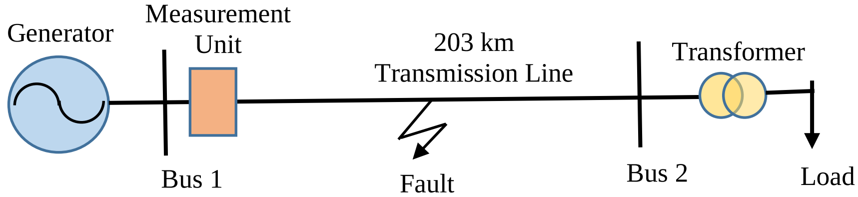

Figure 6. Simulated Transmission Line.

Since there is no open database for power transmission line faults, a transmission line model, given in Figure 6, was designed and simulated with certain parameters in MATLAB/Simulink. The sampling frequency of Simulink model is 10 kHz. In this model, there is a generator, a measurement unit, a transformer, a load and two buses. The base value of the voltage is 154 kV, and the length of the transmission line is 203 km, and some of the other parameters of the transmission line are given in Table 1.

Table 1. Electrical parameters for transmission lines.

Parameter	Positive Sequence	Zero Sequence
Resistance per unit length (Ohms/km)	0,01273	0,3864
Capacitance per unit length (F/km)	$12{,}74.10^{-9}$	$7{,}751.\ 10^{-9}$
Inductance per unit length (H/km)	$0{,}9337.10^{-3}$	$4{,}1264.10^{-3}$

The operating condition of the simulated transmission line is selected as follows:

- Fault resistance are selected from 0 ohm to 150 ohm
- Fault distances are selected among 3 to 200 km from bus 1.
- Inception angles are varied from 0^o to 90^o.
- Fault types are a-g, b-g, c-g, a-b, a-c, b-c, a-b-g, a-c-g, b-c-g, a-b-c, a-b-c-g.

The block diagrams of the fault detection and classification algorithms can be seen in Figure 3 and 4. To show the validity of the PCA and ICA algorithms for fault detection, all possible short circuit fault types were considered, each fault type has 100 fault data, and a fault database with 1100 fault data was created. The threshold values of the PCA and ICA algorithms were found first using the confidence limit definitions, then the accuracies and average fault detection times (AFDT) of the algorithms were obtained by using the database. The results are presented in Table 2. As illustrated in Table 2, the most suitable statistics for the given data are the T^2 statistics for the PCA, and I_e^2 statistics for the ICA.

Table 2. Fault detection rates and times of the statistics

	PCA (%)	ICA (%)	AFDT(ms)
T^2	100	-	0,84
SPE	73	65	0,03
I^2	-	45	0,59
I_e^2	-	100	0,87

Table 3. Fault detection accuracies and times of the classification algorithms.

	SVM		KNN		DT		ANN	
	Accuracy (%)	AFDT (ms)	Accuracy (%)	AFDT (ms)	Accuracy (%)	AFDT (ms)	Accuracy (%)	AFDT (ms)
M	89,86	34	95,13	31,1	95,34	10,4	89,79	7
V	87,09	33,3	90,05	30,3	92,51	12,5	82,81	8,4
K	81,87	50.1	94,41	45,5	93,83	29,6	84,60	25,9
W1	86,01	146,1	92,26	132,8	92,26	166,3	69,69	151
W2	85,05	104,4	92,59	94,8	92,27	74,5	90,86	76,5
W3	83,86	202,1	90,56	183,6	88,98	144,3	79,96	148,1
W4	81,87	187.5	91,61	170,4	89,64	133,9	88,40	137,4

Additionally, to evaluate the accuracy of the fault detection capabilities of the classification algorithms, features from the time domain and time-frequency domain were extracted and analysed. The results are presented in Table 3, while the parameter settings of the classification algorithms are detailed in Table 4. As illustrated in Table 3, the accuracies and fault detection speeds are lower than the PCA and ICA algorithms. ST transform features were not taken into account due to the long calculation time of the ST transformation.

Table 4. Parameter settings of the classification algorithms.

	Parameter Settings
KNN	Number of Neighbors = 4 Distance = Euclidean Distance Weight = Equal Standardize Data = True
SVM	Kernel = Linear Kernel Scale = Automatic Standardize Data = True
DT	Max Number of Split = 100 Split Criterion = Gini’s diversity index
ANN	Layer Size =30 Activations = relu Output Layer Activation = softmax Solver = LBFGS

After the fault detection, the fault classification stage starts to identify the faults. Features can be obtained with different scenarios and methods for fault classification. In this study, one and quarter cycle of the post fault current signals are chosen to extract the features because in case of a fault, the current values increase and are no longer sinusoidal. Energy, entropy, standard deviation, and kurtosis values of ST and WT transformations of current signals in time frequency-domain are used as features. In addition, mean, variance and kurtosis values of one and quarter cycle current signals in time domain are used as features. The features and corresponding labels are given in Table 5.

The efficiency verification of one-cycle features was conducted using SVM, ANN, DT, and KNN classifiers, employing 10-fold cross-validation on the database. The cross-validation method involves randomly dividing the entire dataset into 10 subsets of equal size. Subsequently, a single subset is designated as the test set, while the remaining subsets are utilized as the training set. This procedure is repeated 10 times, and the final result is determined by averaging the outcomes of the 10 iterations.

Table 5. Features and labels.

M	Mean value of one cycle signal in time domain
V	Variance of one cycle signal in time domain
K	Kurtosis of one cycle signal in time domain
$\mathbf{S_1}$	Energy of ST transformed signal
$\mathbf{S_2}$	Standart deviation of ST transformed signal
$\mathbf{S_3}$	Entropy of ST transformed signal
$\mathbf{S_4}$	Kurtosis of ST transformed signal
$\mathbf{W_1}$	Energy of WT transformed signal
$\mathbf{W_2}$	Standart deviation of WT transformed signal
$\mathbf{W_3}$	Entropy of WT transformed signal
$\mathbf{W_4}$	Kurtosis of WT transformed signal

Two studies were conducted for comparison of the performances of the classifiers with different features and feature windows. In the first study, all possible fault types that may occur in the power transmission line were taken into consideration and the classification results were shown in Table 6. It is seen that ICA and PCA algorithms do not affect the classification process since they only estimate faults and the estimation position of the faults are close to each other. Upon verification of the results for accuracy, the superior classification outcomes were achieved utilizing the SVM algorithm, employing the mean value and energy of the ST transformed signal. In terms of the effect of length of feature window, it is seen that the classification results of features with one cycle window length are higher. These results show that for periodic signals, extracting features from one period signal will increase the classification performance of classification algorithms.

Table 6. Comparisons of classification performances of features for one and quarter cycle signal lengths (11 faults).

	Classification Results for PCA with One Cycle Signal Length(%)				Classification Results for ICA with One Cycle Signal Length (%)				Classification Results for PCA with Quarter Cycle Signal Length(%)				Classification Results for ICA with Quarter Cycle Signal Length (%)			
	SVM	**KNN**	**DT**	**ANN**	**SVM**	**KNN**	**DT**	**ANN**	**SVM**	**KNN**	**DT**	**ANN**	**SVM**	**KNN**	**DT**	**ANN**
M	95,7	83,5	93,1	90,9	**96,7**	83,1	93,5	90,9	88,1	82,4	91,4	87,9	89,5	80,7	90,5	86,9
V	95,9	81,8	94,8	90,5	95,9	82,3	93,9	90,9	92,2	81,3	93,1	85,5	91,3	81,3	89,6	86,1
K	93,5	89,6	90,9	91,8	94,4	90,0	91,3	91,3	70,1	77,6	69,1	87,8	77,4	80,7	72,3	86,5
S_1	95,7	82,8	94,8	89,2	**96,5**	83,1	94,4	90,9	91,4	80,9	88,7	84,2	93,75	81,1	92,8	85,2
S_2	91,8	81,5	87,4	89,6	92,2	81,0	89,6	89,6	89,7	80,0	83,1	85,1	90,8	80,4	87,0	84,3
S_3	78,4	68,0	66,2	82,1	79,2	68,4	66,7	83,1	73,7	67,2	60,5	77,8	76,6	65,3	60,9	78,9
S_4	86,6	91,8	90,9	90,2	86,6	92,6	93,5	93,1	85,6	84,3	86,1	85,2	84,6	85,9	85,9	85,6
W_1	87,4	60,0	81,0	81,1	86,1	60,2	81,2	84,1	84,1	59,9	80,9	74,2	85,1	59,0	80,6	75,3
W_2	86,6	77,5	79,7	89,2	88,7	75,3	79,2	90,0	83,2	75,2	78,6	82,5	86,9	72,0	75,9	83,0
W_3	83,3	79,7	72,7	88,7	83,5	80,5	72,3	90,0	74,7	77,6	70,3	83,3	75,4	72,8	68,3	84,1
W_4	72,3	60,8	69,7	65,4	64,9	55,8	63,6	87,0	58,1	56,5	59,1	60,3	56,4	54,6	60,3	61,5

Furthermore, it is also seen that the classification accuracies are lower than 95% for some classifiers. The main reason for this issue is that a-b-c-g and a-b-c faults are similar and not easy to separate these faults from each other. As a solution to this problem, most of the power line fault works suggest using 10 faults for fault classification (Roy & Bhattacharya, 2015; Samantaray, 2013; Upendar, Gupta, & Singh, 2008). Therefore, as the second study, the performances of the classification algorithms were also calculated for only 10 faults (without a-b-c-g), and the results are shown in Table 7.

As can be seen in Table 7, the accuracies of the SVM, KNN, and ANN with the features M, V, and S_1 are increased to 100% for one cycle feature window. The accuracies of the other features are also increased but not as good as the M, V and S_1. On the other hand, M and S_1 features with SVM and KNN algorithms show 100% accuracy for the quarter cycle window. However, the classification accuracies of the other features decrease for the quarter cycle.

Table 7. Comparisons of classification performances for one and quarter cycle signal lengths (10 faults without a-b-c-g)

	Classification Results for PCA with One Cycle Signal Length(%)				Classification Results for ICA with One Cycle Signal Length (%)				Classification Results for PCA with Quarter Cycle Signal Length(%)				Classification Results for ICA with Quarter Cycle Signal Length (%)			
	SVM	**KNN**	**DT**	**ANN**	**SVM**	**KNN**	**DT**	**ANN**	**SVM**	**KNN**	**DT**	**ANN**	**SVM**	**KNN**	**DT**	**ANN**
M	**100**	**100**	98,6	**100**	**100**	**100**	98,6	**100**	**100**	97,1	97,2	95,7	**100**	**100**	97,0	96,3
V	**100**	**100**	98,6	**100**	**100**	**100**	98,1	**100**	98,0	99,0	99,0	95,5	99,0	99,1	96,4	94,3
K	96,2	91,9	94,3	93,3	95,2	93,3	95,2	93,8	84,5	85,4	74,7	91,3	84,6	87,5	77,8	92,1
S_1	**100**	**100**	99,0	**100**	**100**	**100**	99,0	**100**	**100**	**100**	99,0	96,1	**100**	**100**	97,0	96,8
S_2	96,7	96,7	96,7	98,6	95,2	96,7	96,7	95,0	95,0	94,0	99,0	93,3	94,0	95,0	95,0	92,7
S_3	90,5	83,3	81,0	93,3	90,0	82,9	81,0	93,8	86,8	80,0	79,1	79,1	87,5	79,9	75,3	79,6
S_4	98,6	97,6	99,0	98,6	98,6	97,6	99,0	98,1	96,2	94,3	89,3	90,2	96,2	96,2	91,3	91,1
W_1	98,1	71,9	96,7	98,1	98,1	73,8	95,2	95,5	97,2	95,2	93,0	93,4	96,2	72,0	94,2	94,2
W_2	98,1	88,6	96,7	99,5	99,0	90,5	95,2	95,2	98,0	95,2	93,2	92,2	98,1	89,4	93,6	92,8
W_3	95,7	96,2	87,6	97,1	95,7	96,2	89,0	88,1	85,7	86,9	83,8	93,4	90,2	86,3	82,6	93,9
W_4	76,7	77,6	79,0	64,8	72,9	70,5	69,5	72,9	66,3	68,2	70,6	61,4	71,4	69,9	65,1	62,9

5. Conclusions

In this paper, PCA and ICA algorithms, which use only faultless data to find faults, are presented instead of ANN or classification algorithms because they are more appropriate to operate in real-time for detecting faults in a power transmission line. The fault detection performances of these algorithms are 100% with the T^2 and I_e^2 statistics. It is clear from these results that both algorithms are the most suitable algorithms for real-time fault detection in the power transmission line. Furthermore, one cycle signals are suggested to use for feature extraction in the classification. The major benefit of extracting features from one cycle signals is that it guarantees that all time-domain features are the same for faultless data, regardless of where the starting point of the feature is. The results in Tables 6 and 7 also support the use of one cycle time-domain features. The M and V features over one cycle give better classification results than all WT features and most of the ST features. It is seen in Table 7 that the classification performances of M and V are 100% for 10 fault types. Besides, it is observed that the SVM algorithm can be chosen as a classification algorithm for power transmission faults because it has the best results for 10 and 11 fault types.

Statement of Conflicts of Interest

The author declares no affiliations or involvement with any organization or entity with financial or non-financial interests in the subject matter or materials discussed in this manuscript.

Statement of Research and Publication Ethics

The author declares that this study complies with Research and Publication Ethics.

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