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Combined morphology and SVM-based fault feature extraction technique for detection and classification of transmission line faults

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Abstract: A transmission line is the main commodity of power transmission network through which power is transmitted to the utility. These lines are often swayed by accidental breakdowns owing to different random origins. Hence, researchers try to detect and track down these failures at the earliest to avoid financial prejudice. This paper offers a new real-time mathematical morphology based approach for fault feature extraction. The morphological open-close-median filter is exploited to wrest unique fault features which are then fed as an input to support vector machine to detect and classify the short circuit faults. The acquired graphical and numerical results of the extracted fault features affirm the potency of the offered scheme. The proposed scheme has been verified for different fault cases simulated on high-voltage transmission line modelled using ATP/EMTP with varying system constraints. The performance of the stated technique is also validated for fault detection and classification in real-field transmission lines. The results state that the proposed method is capable of detecting and classifying the faults with adequate precision and reduced computational complexity, in less than quarter of a cycle.

Key words: Transmission line protection, fault detection and classification, fault feature extraction, support vector machine, mathematical morphology

1. Introduction

The electric power transmission line is one of the most vital elements of the power system network since it conveys the electricity from generation to distribution end. It goes without saying that the performance of the transmission system plays a pivotal role for continuous power supply. One of the most significant aspects that obstruct the continuous supply of electric power is a fault on power transmission line which is inevitable and way beyond the control of manhood [1]. If a fault is not detected accurately and persists for a while, it may lead to massive destruction or a power outage. Consequently, it is essential to own a more enhanced and well-coordinated transmission line relaying scheme that detects and characterizes any kind of fault efficiently within the destined time for assisting fleet repair and restoration of the power supply with least disruption [2, 3]. As a consequence, plenty of scholarly research has been forced to develop a robust, precise and intelligent scheme for fault detection and classification on transmission lines.

In literature, the fault detection and classification techniques are generally divided into two categories as: 1) the conventional techniques and 2) machine-learning (ML)-based techniques. Owing to the tricky mathematical calculations, the conventional techniques have a large computational complexity that depends on the size of the power system. In terms of speed and accuracy, the ML-based techniques are found to be more

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Nomenclature:

R_F	: Fault resistance	D_F	: Fault Location
Z_S	: Source Impedance	X_0	: DDC magnitude
X	: Magnitude of sinusoidal component	ω	: Angular frequency
τ	: DDC time constant	f_s	: Sampling frequency
A_1	: Magnitude of fundamental component	ϕ_1	: Phase angle of fundamental component
m	: Harmonic order	σ	: Standard deviation
Δt	: Sampling interval	N	: Number of samples per cycyle
ΔD	: Extracted fault feature vector	T_t	: Training time in (ms)
T_r	: Response time in (ms)	R_0	: Zero sequence resistance of line in (ohm/km)
R_1	: Positive sequence resistance of line in (ohm/km)	R_2	: Negative sequence resistance of line in (ohm/km)
L_0	: Zero sequence inductance of line in (mH/km)	L_1	: Positive sequence inductane of line in (mH/km)
L_2	: Negative sequence inductance of line in (mH/km)	C_0	: Zero sequence capacitance of line in (μF/km)
C_1	: Positive sequence capacitance of line in (μF/km)	C_2	: Negative sequence capacitance of line in (μF/km)
ΔD_x	: Extracted fault feature vector for signal X	ΔD_y	: Extracted fault feature vector for signal Y
ΔDi_0	: Extracted fault feature vector for zero sequence current	ΔDi_1	: Extracted fault feature vector for phase A current
ΔDi_2	: Extracted fault feature vector for phase B current	ΔDi_3	: Extracted fault feature vector for phase C current
ΔDv_0	: Extracted fault feature vector for zero sequence voltage	ΔDv_1	: Extracted fault feature vector for phase A voltage
ΔDv_2	: Extracted fault feature vector for phase B voltage	ΔDv_3	: Extracted fault feature vector for phase C voltage

efficient for detecting and classifying transmission line faults [4, 5]. The first step of ML-based techniques is the training of the classifier. The classifier needs to be trained by the extracted values for the particular fault features, acquired from the simulations of several fault scenarios in reliable softwares like MATLAB, PSCAD, ATP-EMTP, etc. Later, the new fault cases can be detected and classified easily with the help of this trained classifier [6].

Numerous signal processing techniques such as Fourier transform (FT), wavelet transform (WT), stock well transform (ST), hilbert-huang transform (HHT), principal component analysis (PCA), empirical mode decomposition (EMD), etc. have been stated in the literature for fault feature extraction. All these techniques are computationally more complex and time-consuming as the tricky computations of transform coefficients, related to the different aspects of fault signals and faulty conditions have to be performed within a sampling interval. Because of these, most of these techniques face problems regarding speed, accuracy, reliability, computational complexity, etc. Also, each of these techniques has pros and cons as listed in Table 1 [4–7]. ML-based techniques i.e. artificial neural network (ANN), k-nearest neighbor (kNN), and support vector machine (SVM) combined with the abovementioned feature extraction techniques are used for detecting and classifying the faults [8–21].

Table 1. Pros and cons of the existing feature extraction techniques.

Feature extraction technique	Pros	Cons
FT	i) A simple and widely used method for the steady-state analysis of the stationary signals.	i) Cannot be used for nonstationary signals.
WT	i) Perfectly suitable where time and frequency information is required.	i) Highly sensitive to noise and harmonics.
	ii) Does not need to assume the periodicity of the signal.	ii) More computational requirements with high sampling rate.
		iii) Time-consuming as the choice of appropriate mother wavelet and the number of decomposition level must be performed by a trial-and-error process.
ST	i) Good time-frequency resolution and noise immunity.	i) Not suitable for real-time applications.
	ii) Provides information on time, frequency and the phase angle of the signal.	ii) ST coefficients over all the frequency components need to be calculated for each specified time value, which requires a large amount of calculation time and memory.
HHT	i) Extracts the features by generating a quadrature waveform hence able to mark changes in the amplitude and phase.	i) Not applicable for wideband signals.
	ii) Works well with both stationary and nonstationary signals.	ii) High computational complexity.
	iii) Requires no initial assumption of the signal and hence are adaptive to any unknown signals.	
PCA	i) A simple and fast method.	i) The covariance matrix can be endlessly large if the number of dimensions is greater than the number of data points.
	ii) Minimize the reprojection error.	ii) Difficult to obtain exact covariance matrix.
	iii) Reduces the dimensionality of the data.	
	iv) Immune to noise.	
EMD	i) An adaptive and fully data-driven technique.	i) The main drawback is the mode mixing that leads to loss of data during the process of signal denoising.
	ii) No need to preset the level of decomposition and hence overcomes the intrinsic limitations of WT.	ii) The method requires many iterations and numerous calculations.
	iii) Does not require a predetermined set of mathematical functions.	

In [8–12], WT together with ANN is used for fault detection and classification on the transmission line. In [13], a combination of ST and ANN is used for detecting and classifying faults on the overhead transmission line. Even if the ANN-based techniques have been quite efficient in identifying the fault types, it suffers from lots of drawbacks as follows:

- Accuracy depends on the number of extracted fault features.
- Parameter tuning is quite difficult as the large number of parameters needs to be optimized and the exact procedure for doing so is not defined as a result ANN is still a black box which lacks the transparency.
- Time consuming learning process as the considerable amount of sampled data and training efforts are needed for good performance particularly under wide variations of system parameters (fault resistance, source impedance, etc.) leading to increase the computational complexity as well and hence limits the applications of ANN-based schemes.
- In some cases, training may not converge due to random selection of starting point and hence gets stuck on local minima which ultimately affects the overall performance.

Despite ANN, SVM-based schemes have more advantages as follows:

- Accuracy is independent of the number of extracted fault features and hence is more suitable for fault analysis in transmission line where less parameters are available with the utilities.
- The optimal factors can be easily selected by the cross-validation method and hence has a good classification ability and robustness.
- Owing to high training speed and better generalization properties, frequently used for the classification problems and offers a global solution.
- Possibility of over-fitting is avoided since it minimizes the structural risk in place of empirical risk.

Hence, SVM combined with abovementioned feature extraction techniques have been widely used for fault detection and classification on the transmission line. In [14–17], fault features extracted using WT are used as input to SVM for classifying faults on the transmission line. In [18], efficient and reliable detection of faults on the transmission line is achieved from the fault features extracted using ST analysis further SVM is deployed for identifying a fault type. One more approach combining PCA with SVM for fault diagnosis in the power transmission line is reported in [19]. A hybrid HHT-SVM and EMD-SVM based fault detection and classification techniques are stated in [20] and [21], respectively.

However all these feature extraction techniques have been used for classifying the fault types with different patterns, considerable preceding information of the particular system pattern is essential. The process of obtaining these details require constant amendments and corrections which can turn out to be a time-taking process and also lacks generalizability [22]. Also, the main drawback of most of the techniques used for fault feature extraction is that it fails to extract the features precisely in presence of decaying DC component (DDC), noise and severe harmonic conditions. This implies that the main issue in ML-based techniques is the extraction of the fault features from the power system signals (i.e. voltage or current). If the technique used has high computational complexity and significant time delay, it can affect the overall speed and accuracy of the fault detection and classification technique [22]. Consequently, in order to achieve the highest accuracy, an effective technique is desirable for preprocessing and generating the most relevant features from the voltage or current waveforms witnessed during the fault with minimum delay.

Mathematical morphology (MM) is a time-domain signal processing method that precisely extracts apart from any distortions with reduced size of data window in real-time [23–25]. In the literature, MM-based methods are not intended for the purpose of fault feature extraction. Hence, to tackle the hassle of computational complexity and time-delay in fault-feature extraction, a new, simple, fast and powerful real-time fault feature extraction technique based on MM is proposed in this paper. Moreover, SVM is a robust ML technique that determines an optimal hyper-plane using the statistical learning theory and optimization theory to exploit the generalization ability of the classifier. It has a relatively good classification ability and is independent of the number of features used for the dataset generation [26–28]. Hence, the proposed method is combined with SVM to have the speedy and precise fault detection and classification in power transmission lines.

The proposed approach works in three steps. First of all, the sampled 3-phase current signals along with zero sequence current acquired from the sending-end of transmission line are preprocessed using morphological open-close-median filter (OCMF) to obtain the relevant fault features. In the second step, these extracted features are used to train multiclass SVM (MCSVM). Afterwards, this trained classifier is used to detect and classify the different fault types. Unlike the other techniques, the proposed methodology of combining OCMF with MCSVM for fast, robust and reliable fault detection and classification is nowhere reported in the literature. As far as our knowledge, this is the first attempt of combining the MM-based OCMF with MCSVM. This work exhibits the following contributions:

- OCMF-based new, easy, fast and robust real-time fault feature extraction technique with reduced time delay, computational complexity and data window size which works effectively in presence of DDC, noise and severe harmonic conditions as well.
- Comparison of the proposed feature extraction technique with other existing techniques.
- Combined OCMF and MCSVM-based intelligent recognition technique geared towards both the fault detection and classification in power transmission line.
- Validation of the proposed OCMF-based feature extraction technique to accomplish the speedy and precise fault diagnosis by combining it with other two techniques such as ANN and kNN.
- Validation of the performance of the proposed OCMF-MCSVM-based fault detection and classification technique by using both simulated and real-field data.

Numerous simulation studies for all types of shunt faults (SLG, LL, LLG, LLL and LLLG) have been performed using a system built in ATP/EMTP for dataset generation. Several training and test cases are simulated with altered combinations of fault types and varying system constraints such as fault inception angle (FIA), R_F, D_F, Z_S etc. Since the proposed method needs only four features for detecting and classifying the faults, the memory requirement and computational time will substantially reduce. Also, the proposed feature extraction technique involves only addition and subtraction, henceforth has a reduced computational intricacy compared to others and hence offers the promising results without sacrificing the speed. The obtained results reveal that the proposed technique offers a straightforward and effective means to detect and classify the transmission line faults effectively.

The subsequent topics addressed in remainder of this paper are: Section 2 deals with brief outlines of the MM and SVM fundamentals. In Section 3, the mathematical framework of the proposed OCMF-MCSVM-based fault detection and classification technique along with the flowchart is further elaborated. The validation of the proposed approach using both simulated and real-field data is discussed and compared with existing methods in Section 4. At last, Section 5 puts forward some concluding remarks.

2. Preliminaries

2.1. Basics of mathematical morphology (MM)

MM is a deep-rooted nonlinear waveform analysis technique offered by Matheron and Serra to facilitate the extraction of vital and most relevant features of the signals using a suitable function called the structuring element (SE) [26]. SE glides through the signal like a moving window and extricates the peculiar features in the neighborhood of each sample in the signal. The shape and size of SE contribute significantly in such type of analysis thus should be selected as per the requirement and aim of the particular application. Owing to the availability of mostly one-dimensional signals, flat SE is suitable for several power system applications. MM is completely different from the integral transform-based approaches in basic principles, mathematical operations and also have lots of advantages as follows:

- Rapid and easy-peasy computations i.e. subtraction, addition, minimum and maximum.
- High speed and lucid processing with much-reduced data window size, henceforth suitable for real-time applications.
- Applicable to nonperiodic transient signals.
- Time-domain signal processing technique which extracts the most relevant features accurately despite any deformity.

For signal processing, MM employs two basic operations i.e. dilation and erosion, defined as follows:

Let $X(i)$ and $S(j)$ be input signal to be processed and the SE, defined in the domains, $D_x = \{m_0, m_1, ..., m_i\}$ and $D_s = \{n_0, n_1, ..., n_j\}$, respectively with $i > j$ where i and j are integers. The dilation of $X(i)$ by $S(j)$ denoted by $X \oplus S$ is given by:

$$DI = (X \oplus S)(i) = max\{X(i-j) + S(j)\}, \qquad (i-j) \in X,\ j \in S \tag{1}$$

In the same way, the erosion of $X(i)$ by $S(j)$ denoted by $X \ominus S$ is given by:

$$ER = (X \ominus S)(i) = min\{X(i+j) - S(j)\}, \qquad (i+j) \in X,\ j \in S \tag{2}$$

Based on these two basic operators, opening and closing operators are defined as:

$$Open = (X \circ S)(i) = ((X \ominus S) \oplus S)(i). \tag{3}$$

In the same way, the closing of by denoted by is given by:

$$Close = (X \bullet S)(i) = ((X \oplus S) \ominus S)(i). \tag{4}$$

Though MM operations have been mainly offered and implemented for image processing, they have been applied for power system applications as well [27]. Proper utilization of these operations can easily wrench out the most relevant and meaningful features from the power system signal captured during a fault. Hence for the purpose of fault feature extraction, based on these two operations, a morphological open-close-median filter (OCMF) is defined as:

$$OCMF = \frac{(X \circ S)(i) + (X \bullet S)(i)}{2}. \tag{5}$$

2.2. Basics of support vector machine (SVM)

SVM is a robust, powerful and handy technique, firstly introduced by Vapnik and Cortes to resolve the classification challenges in statistical learning theory and structural risk minimization [23]. The prime objective of this technique is to figure out an optimal hyper-plane that splits dataset into two classes [24] as shown in Figure 1. In the absence of optimal hyper-plane, the aim of SVM is to maximize the margin and to minimize the number of errors. This hyper-plane is obtained by solving the optimization problem [25] as:

$$f(\omega, \xi) = \begin{cases} \min\limits_{\omega} \dfrac{1}{2}|\omega|^2 + C\left(\displaystyle\sum_{i=1}^{l} \xi_i\right) \\ \text{s.t.} \quad y_i\left(\omega \cdot x_i + b\right) \geq 1 - \xi_i, \quad \xi_i \geq 0 \forall i \end{cases} \tag{6}$$

where x_i and y_i are the case and the class label ± 1. The solution of (6) is obtained from the following dual as:

$$\begin{cases} \max L_d = \displaystyle\sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j k\left(x_i, x_j\right) \\ \text{s.t.} \quad 0 \leq \alpha_i \leq C \forall i, \quad \sum_i \alpha_i y_i = 0 \end{cases} \tag{7}$$

where $k\left(x_i, x_j\right)$ is a nonlinear kernel function. The four different types of kernel functions i.e. linear, polynomial, sigmoid, and radial basis function (RBF) are stated in the literature [16]. The aforementioned mathematical analysis states that SVM is basically developed for binary classification. Hence, SVM is further modified to address the multiclassification problems. For this, two types of tactics are defined as: 1) to amend the designed SVM model to include the multiclass learning in the quadratic solving algorithm and 2) to blend numerous binary classifiers [25]. The later one involves the techniques like one-versus-all (OVA) and one-versus-one (OVO). In this paper, owing to the high accuracy and less training time, OVO approach with RBF kernel is applied for classification of different types of shunt faults occurring on power transmission line.

3. Proposed approach

The step-by-step basis of the proposed methodology developed to extract the fault features and identify the fault types is outlined in this section. The schematic drawing and flowchart are portrayed in Figure 2. It works in three phases i.e. feature extraction, feature selection and fault classification. In the first phase, once the entire system is simulated considering the several fault conditions by varying the system parameters, the fault features are extracted using a proposed OCMF-based feature extraction technique. Phase two consists of feature selection, and is named attribute selection. It entails the hunt for all probable blends of the extracted features to ascertain a particular feature subset having a fine prediction or classifying aptitudes. Later, the selected set of extracted features with known relevant classes is given as an input to MCSVM built using numerous binary SVM to classify the new test cases.

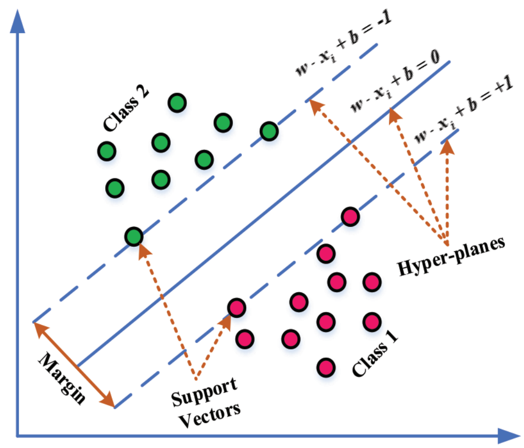

Figure 1. Optimal hyper-plane for SVM classification.

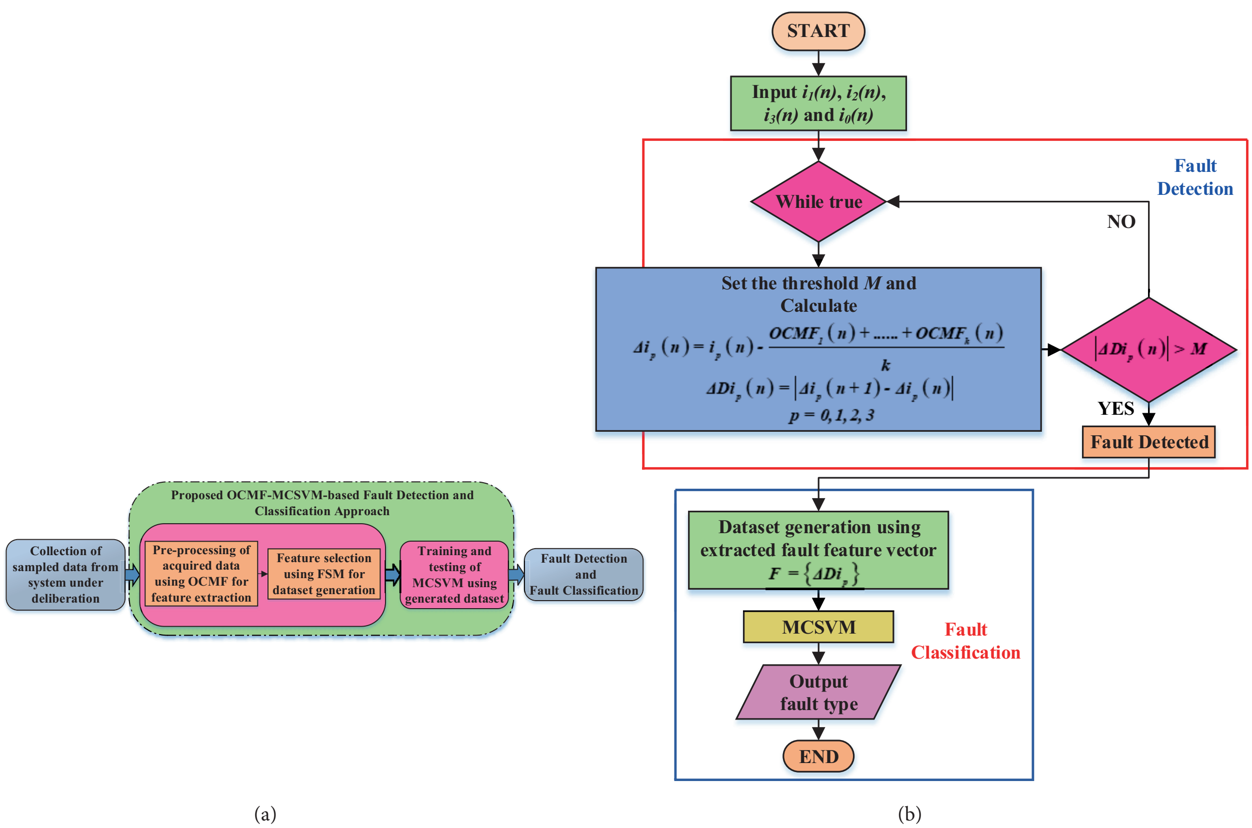

Figure 2. Proposed OCMF-SVM-based fault detection and classification technique (a) general block diagram, (b) flowchart.

3.1. Feature extraction

The basis of the majority of the detection and classification techniques lies in a fine dataset of fault features. The set of relevant features should be small-sized, and has a low computational complexity. Generally, in real-world applications, the relevant features are suppressed in redundancy and noise, hence it is desirable to excerpt this info in cost-effective ways without losing the valuable data. Morphological filters can precisely extract the features characterized by the SE and obtain a signal with merely part of concern through distinct MM operators [27]. A flat linear SE and an averaging filter named OCMF designed using two basic MM operators, i.e. dilation and erosion, are used for feature extraction. The detailed mathematical analysis is explained in this subsection as follows:

Whenever fault arises in the power system, the fault signal can be expressed as a combination of steady-state sinusoidal component and an exponentially decaying DC (DDC) component. Hence, mathematically it can be stated as:

$$x_f\left(t\right) = X_0 e^{-t/\tau} + X cos\left(\omega t + \phi\right). \tag{8}$$

Now, after sampling the signal $x_f\left(t\right)$ at f_s, the k^{th} sample of $x_f\left(t\right)$ can be expressed as:

$$X_f\left(k\right) = X_0 e^{k\lambda\Delta t} + X cos\left(\delta k + \phi\right), \tag{9}$$

where $\lambda = -1/\tau$, $\delta = \omega\Delta t$ and $t = n\Delta t$.

According to first-order Taylor series expansion, equation (9) can be expressed as:

$$X_f\left(k\right) = X_0 + \lambda k\Delta t + X cos\left(\delta k + \phi\right). \tag{10}$$

If this expansion occurs at a centre point $X_f\left(k\right)$, then its left and right side samples can be expressed as:

$$X_f\left(k-n\right) = X_0 + \lambda(k-n)\Delta t + X cos\left((k-n)\cdot\delta + \phi\right), \tag{11}$$

$$X_f\left(k+n\right) = X_0 + \lambda(k+n)\Delta t + X cos\left((k+n)\cdot\delta + \phi\right). \tag{12}$$

Adding equations (11) and (12),

$$X_f\left(k-n\right) + X_f\left(k+n\right) = 2X_f\left(k\right) cos\left(n\delta\right) + 2\left(X_0 + \lambda k\Delta t\right)\cdot\left(1 - cos\left(n\delta\right)\right). \tag{13}$$

If n is a small integer, then for high f_s, $cos\left(\omega\cdot n\Delta t\right) = cos\left(n\delta\right) \approx 1$. Hence, equation (13) can be approximated as:

$$X_f\left(k-n\right) + X_f\left(k+n\right) \approx 2X_f\left(k\right), \tag{14}$$

$$X_f\left(k\right) \approx \frac{X_f\left(k-n\right) + X_f\left(k+n\right)}{2}. \tag{15}$$

Fault events on transmission lines create transient disturbances to current and voltage signals. As mentioned in Section 2.1, the most relevant and meaningful features of these disturbances can be easily wrenched out by proper utilization of morphological operators. For this, an averaging filter named OCMF with a flat linear SE defined as $S\left(n\right) = \left[s_n\right] = \left[s_1, s_2, s_3, ..., s_n\right] = \left[0.01, 0.01, ..., 0.01\right]$ is utilized.

For signal $X_f\left(k\right)$, the dilation and erosion operations can be described as:

$$DI = X_f \oplus S = \max_n\left\{x_f\left(k-n\right) + s_n\right\}, \forall n = 1, 2, ..., m \tag{16}$$

$$ER = X_f \ominus S = \min_n\left\{x_f\left(k+n\right) - s_n\right\}, \forall n = 1, 2, ..., m \tag{17}$$

From (16) and (17), the OCMF can be expressed as:

$$OCMF_n(k) = D_n(k) = \frac{open + close}{2} = \frac{(((X_f \ominus S) \oplus S) + ((X_f \oplus S) \ominus S))}{2}. \tag{18}$$

For $n = 1$, equation (18) can be stated as:

$$D_1(k) \approx X_f(k). \tag{19}$$

Now, the difference between $X_f(k)$ and $D_n(k)$ where $n = 1, 2, ..., m$ can be calculated as:

$$\Delta X_f(k) = X_f(k) - \frac{D_1(k) + D_2(k) + ... + D_m(k)}{m}. \tag{20}$$

Based on (20), the OCMF output is constructed as:

$$\Delta D_n(k) = |\Delta X_f(k+1) - \Delta X_f(k)|. \tag{21}$$

A fault onset is perceived if $\Delta D_n(k)$ outstrips the threshold value M. The value of M is preset with consideration of system operating conditions and relies on the flow of fault signals through the transmission line. It is reliant on the noise amplitude rather than that of the current. Depending on the system operation condition, the fault current magnitude may significantly rise or fall accordingly, which causes a significant change in noise amplitude. Hence, for such cases, the preset threshold M is calculated based on the root mean square (RMS) value of the fault currents measured by the relay [23].

3.2. Attribute selection

The data features used to train the ML classifiers have a huge impact on model performance. Unrelated or partly relevant features can adversely affect the model performance. Hence, attribute selection is one of the most important steps to be performed. It is a way of opting a subset of pertinent features to build a precise predictive model. Best feature selection helps in enhancing the learning accuracy. If the relevant feature subset is elected, it detracts the training time, computational intricacy as well as over-fitting.

In accordance with (21), the fault features are extracted for all the phase and zero sequence voltages and currents and expressed as $\Delta Di_p(k)$ and $\Delta Dv_p(k)$ respectively where $p \in P = \{0, 1, 2, 3\}$ corresponds to the values of phase A, B, C and zero sequence current and voltage signals. Here, the classifying strength of the extracted features is determined with the help of basic feature selection measures (FSM) i.e. (i) information gain, (ii) univariate feature selection and (iii) recursive feature elimination.

3.2.1. Information gain (IG)

IG quantifies how much knowledge a feature offers regarding the class, hence helps to decide which variable in the available set of training attribute is the most significant for the classification by evaluating the gain of each variable in the context of the target variable. The set of attributes which maximizes the IG is elected [22].

3.2.2. Univariate feature selection (UFS)

This is a robust approach to enhance the classifier performance and to ease the intricacy as well as computing cost. Each attribute is verified singly and compared with the target variable to see if there is any statistically significant relationship among them. Univariate statistical tests are performed to cull those input variables that have a firm relationship with the output variables. The set of features with the highest scores is chosen.

3.2.3. Recursive feature elimination (RFE)

This is a self-indulgent technique that intends to identify the most effective attribute subset. It iteratively builds a model and identifies the best or worst acting features at each repetition. The importance of each feature is obtained either through *a coef_ attribute* or through *a feature_importances_ attribute* and the features with least importance are eliminated from the initial feature set. Later, it ranks the attributes according to the sequence of their removal. The features marked with rank one are elected.

As mentioned earlier, the effectiveness of the extracted features is examined with the help of four basic FSM and the results are given in Table 2. From Table 2, it is clarified that the set $\Delta Di_p(k)$ has the best classifying strength over $\Delta Dv_p(k)$. Hence $\Delta Di_p(k)$ is used for composing the fault feature vector F_i.

Table 2. Ranking of the extracted features.

Feature	IG	UFS	RFE
ΔDi_0	0.71	920.857	1
ΔDi_1	0.35	861.015	1
ΔDi_2	0.39	825.287	1
ΔDi_3	0.42	841.652	1
ΔDv_0	0.29	735.205	2
ΔDv_1	0.33	631.615	5
ΔDv_2	0.27	677.263	4
ΔDv_3	0.28	659.250	3

3.3. Fault classification

Later, the hand-picked set of extracted attributes with known relevant classes is given as an input to the MCSVM to classify the new test cases. Extracted features are also assayed using other ML classifiers as ANN and kNN. For this, classification accuracy (CA) is computed as:

$$CA = \frac{Accurate\ fault\ clasification}{Number\ of\ samples\ tested} \times 100. \tag{22}$$

4. Performance evaluation

In this section, with an eye to affirm the potency of the proposed technique for feature extraction as well as fault detection and classification, varied analytical and simulation test are performed. The performance is assessed from the perspectives of feature extraction time, group delay, computational complexity, classifier performance, and classification time. The feasibility of the proposed technique is validated using real-field data as well to prove its aptness for real-time applications.

4.1. Application to deviation finding of a sine wave

In this subsection, to assay the discriminating aptness of the proposed OCMF-based feature extraction technique, two speculative sinusoidal signals are considered as portrayed in Figures 3a and 3b, respectively. The signal signifies a fault waveform and is composed of a fundamental component, harmonics, and DDC; conversely, the signal is relatively pure. Mathematically, both the signals can be expressed as:

$$X(t) = |A_1| \, cos(\omega_1 t + \phi_1), \tag{23}$$

$$Y(t) = \underbrace{A_0 e^{-t/\tau}}_{DDCComponent} + \underbrace{\sum_{m=1}^{M} |A_m| \, cos(m\omega_1 t + \phi_1)}_{Fundamental+Harmonics} + \underbrace{\xi(t)}_{Noise}. \tag{24}$$

After discretization, equation (23) and (24) can be expressed as:

$$x(n) = |A_1| \, cos\left(\frac{2\pi}{N} n + \phi_1\right), \tag{25}$$

$$y(n) = A_0 e^{-n\Delta t/\tau} + \sum_{m=1}^{(N/2)-1} |A_m| \, cos\left(\frac{2\pi m}{N} n + \phi_m\right) + \xi(n\Delta t), \tag{26}$$

where $t = n\Delta t$, in a discrete domain. Higher order harmonics (higher than $(N/2) - 1$) are supposed to be screened out with a low pass filter to avoid aliasing.

The proposed OCMF-based technique is applied to both the signals. The extracted features of both the waveforms $\Delta D_x(n)$ and $\Delta D_y(n)$ are depicted in Figure 3c. It has been found that the time for the sudden switch in the magnitude is perceived through the spike. By virtue of noise immunity of OCMF [28], even though $\Delta D_y(n)$ have some low ripples owing to the presence of noise in Y, it can still be applied for sensing a sudden switch in the magnitude of the signals.

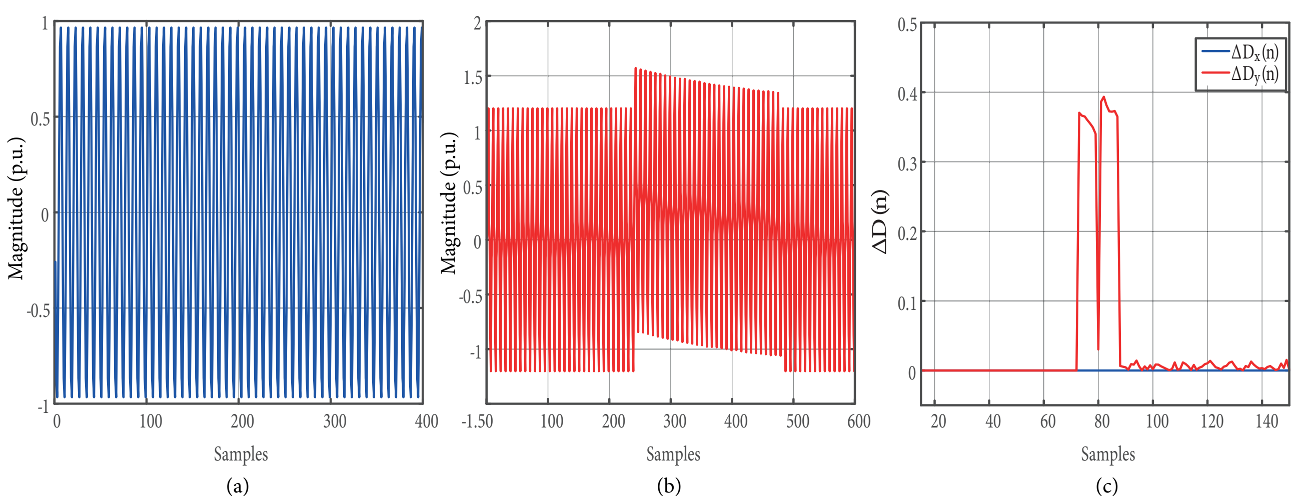

Figure 3. Deviation finding of sinusoidal waveform (a) pure sinusoidal signal, (b) simulated fault signal, (c) extracted features using OCMF.

4.2. Application to EMTP-generated signals

In this subsection, a typical 400 kV, 50 Hz, 150 km long overhead transmission line with the parameters described in Table 3 is modelled using ATP/EMTP. The single line diagram (SLD) of the system under deliberation is shown in Figure 4. All the data is amassed from the sending end. The fault current signals acquired from the relaying point at a sampling rate of 1200 kHz are fed to OCMF for feature extraction. The set of extracted features is used for creating the fault feature vector/dataset which is further exploited for training and testing of the proposed OCMF-MCSVM-based fault detection and classification technique. For this, simulations of both symmetrical and unsymmetrical faults are carried out by deviating the system parameters (FIA, R_F, Z_S and D_F) as shown in Table 4.

Table 3. Parameters of 400 kV, 50 Hz, 150 km long overhead transmission line.

Sequence	Parameters	Value	Unit
Positive and negative sequence	R_1, R_2	0.0205	ohm/km
	L_1, L_2	0.9595	mH/km
	C_1, C_2	0.0127	μF/km
Zero sequence	R_0	0.1627	ohm/km
	L_0	3.3868	mH/km
	C_0	0.0099	μF/km

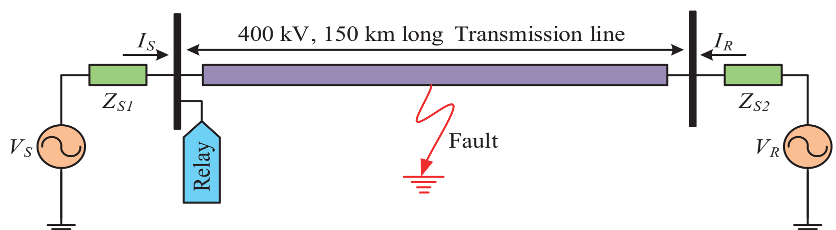

Figure 4. Single line diagram of the system under deliberation.

Table 4. Fault cases simulated for training and testing of MCSVM.

System constraints	Training	Testing
Fault location (D_F)	1 km–150 km in steps of 20 km	1 km–150 km
Fault inception angle ($FIA-\phi°$)	0°, 30°, 45°, 60°,90°	0°-90°
Fault resistance (R_F)	0 Ω – 20 Ω in steps of 5 Ω	0 Ω – 20 Ω
Source impedance (Z_S)	Z_{S1}=100%, Z_{S2}= 10 %-100 % in steps of 25	Z_{S1}=100%, Z_{S2}=10 %-100 %
Fault type	LG, LL, LLG, LLL, LLLG, no fault situations	LG, LL, LLG, LLL, LLLG, no fault situations

Owing to the figure constraints, the simulated fault current signal and the extracted features ΔDi_p only for LG fault at $D_F = 40\ km$ and $100\ km$ on phase 'A' and LL fault at $D_F = 40\ km$ and $100\ km$ on phase 'AB' with varying system constraints for few cases only are depicted in Figures 5 and 6. The acquired values of ΔDi_p for the same are reported in Table 5. It is observed that the value of ΔDi_p for the faulted phase is high and exceeds the threshold value as mentioned in subsection 3.1, while it is low for that of healthy phase.

Hence, the obtained results demonstrate that the extracted fault feature vector $F = \{\Delta Di_p\}, p = 0,1,2,3$ can be used for both fault detection and faulty phase selection as well. Later, this extracted feature dataset with known pertinent classes is fed to MCSVM classifier as an input to categorize the new test cases.

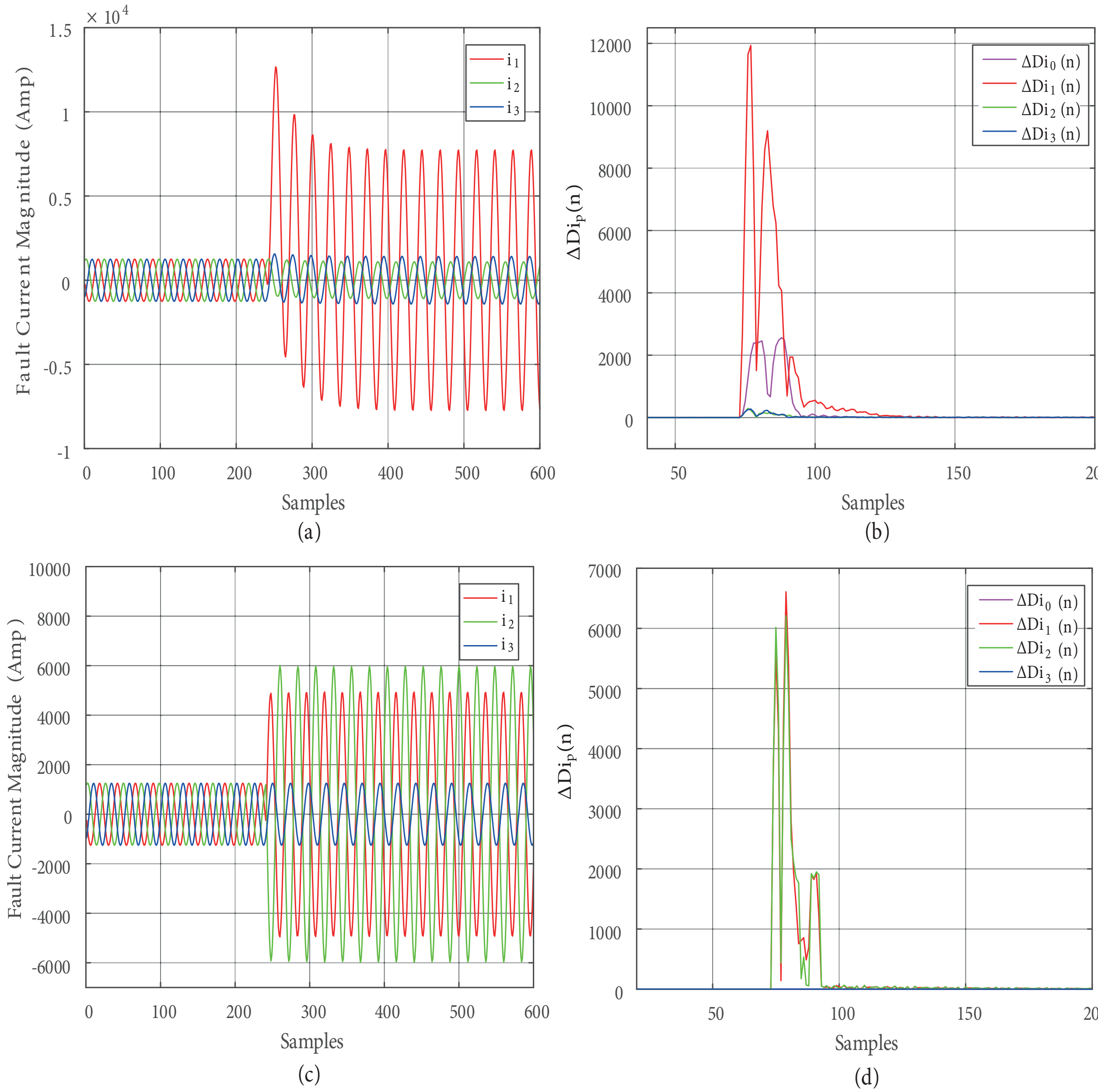

Figure 5. Simulated fault current waveforms and the extracted features in case of LG and LL fault (a) AG fault at D_F=40 km with FIA=0°, R_F=0 Ω, (b) Extracted ΔDi_p for AG fault, (c) AB fault at D_F=40 km with FIA=0°, R_F=20 Ω, (d) Extracted ΔDi_p for AB fault.

Fault classes are ranked as 0(no fault), 1(AG), 2(BG), 3(CG), 4(AB), 5(BC), 6(AC), 7(ABG), 8(BCG), 9(ACG), 10(ABC), 11(ABCG). The results obtained for both the tactics (i.e. OVO and OVA) are stated in Table 6. Obtained results prove the aptness of the proposed OCMF-MCSVM-based technique for the hasty,

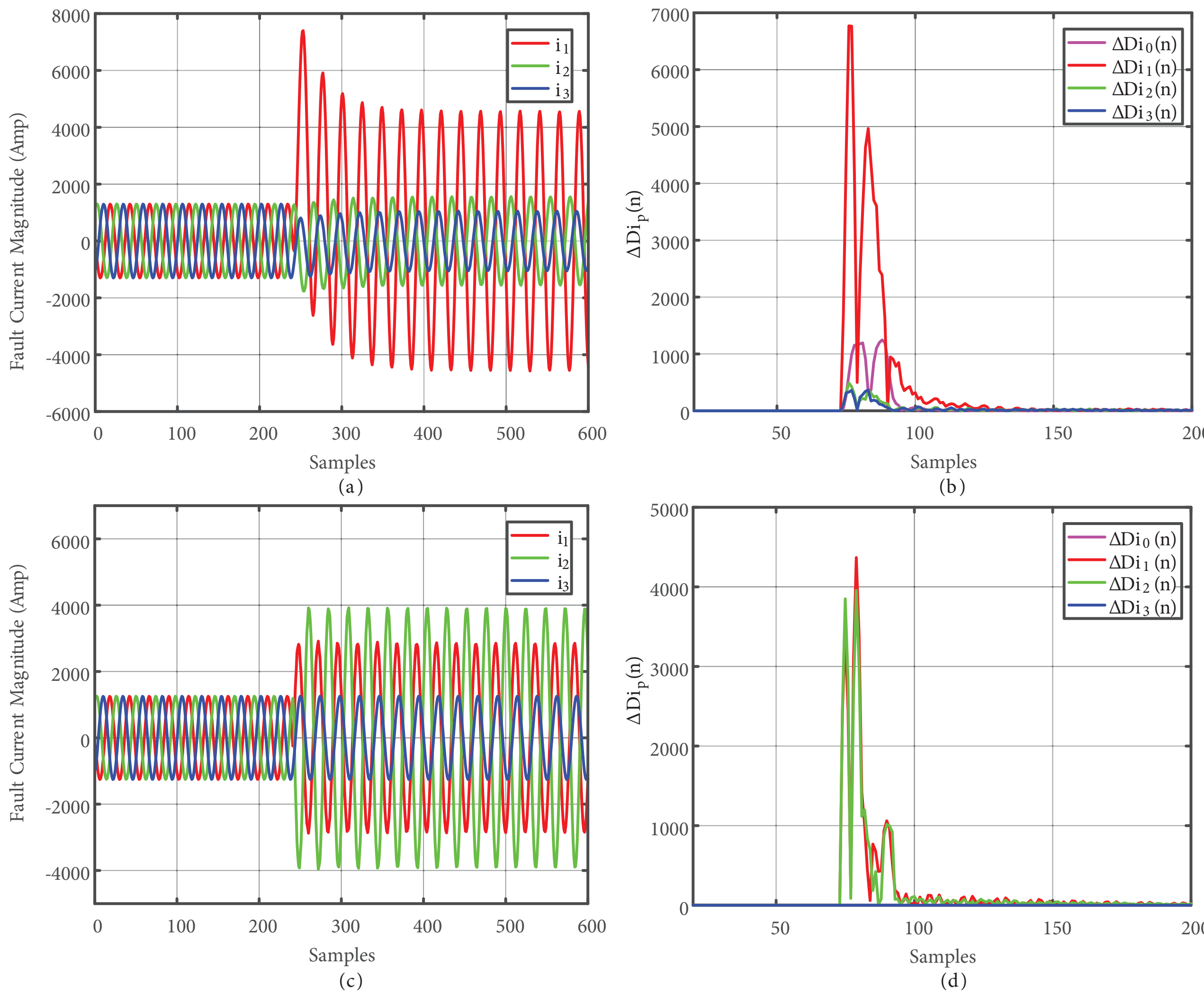

Figure 6. Simulated fault current waveforms and the extracted features in case of LG and LL fault (a) AG fault at D_F=100 km with FIA=0°, R_F=0 Ω, (b) Extracted ΔDi_p for AG fault, (c) AB fault at D_F=100 km with FIA=0°, R_F=20 Ω, (d) Extracted ΔDi_p for AB fault.

precise and unfailing detection and classification of transmission line faults. As the proposed technique avails a two-sample data window, the fault detection and classification is achieved in less than the quarter of the cycle. The potency of the offered combined OCMF-based feature extraction scheme is compared with the other existing techniques WT+SVM [15], PCA+SVM [19], determinant function combined with SVM (DF+SVM) [22] from the perspectives of group delay, data window size and CA. The obtained results are revealed in Table 7.

Table 5. Extracted fault feature vector using OCMF.

Parameters	Fault type	ΔDi_0	ΔDi_1	ΔDi_2	ΔDi_3	Parameters	Fault type	ΔDi_0	ΔDi_1	ΔDi_2	ΔDi_3
FIA=0°, R_F=0 Ω, D_F=40 km	AG	**155.06**	**495.32**	42.34	64.68	FIA=0°, R_F=20 Ω, D_F=40 km	AG	**109.98**	**299.38**	27.79	42.42
	BG	**141.74**	50.89	**381.82**	61.49		BG	**106.82**	40.97	**231.04**	44.63
	CG	**151.65**	50.43	42.24	**458.36**		CG	**109.79**	37.27	24.22	**305.74**
	AB	0.0020	**603.25**	**583.55**	0.7228		AB	0.0020	**295.26**	**271.77**	0.7239
	BC	0.0020	0.6743	**443.02**	**476.17**		BC	0.0020	0.6750	**247.85**	**267.37**
	AC	0.0020	**626.45**	0.6161	**646.50**		AC	0.0020	**305.97**	0.6165	**328.45**
	ABG	**117.48**	**655.51**	**526.29**	42.63		ABC	**96.50**	**317.71**	**289.66**	69.54
	BCG	**124.92**	62.66	**441.95**	**534.79**		BCG	**91.77**	34.00	**265.73**	**383.64**
	ACG	**109.55**	**656.93**	28.11	**648.97**		ACG	**88.64**	**377.26**	26.93	**353.83**
	ABC	0.0008	**798.05**	**585.72**	**661.34**		ABC	0.0010	**345.41**	**254.68**	**377.65**
	ABCG	**42.03**	**667.00**	**544.86**	**703.91**		ABCG	**35.28**	**345.59**	**316.01**	**360.61**
FIA=0°, R_F=0 Ω, D_F=100 km	AG	**75.14**	**286.33**	35.42	42.68	FIA=0°, R_F=20 Ω, D_F=100 km	AG	**53.99**	**174.33**	21.76	31.16
	BG	**68.28**	40.38	**221.45**	51.56		BG	**52.42**	28.62	**159.40**	41.46
	CG	**74.32**	48.47	48.30	**314.97**		CG	**54.10**	31.05	27.59	**193.16**
	AB	0.0010	**340.17**	**349.83**	0.7026		AB	0.0010	**208.95**	**204.74**	0.7022
	BC	0.0010	0.6710	**376.19**	**402.65**		BC	0.0010	0.6709	**200.32**	**223.10**
	AC	0.0010	**407.78**	0.6322	**450.49**		AC	0.0010	**225.01**	0.6314	**266.93**
	ABC	**57.85**	**420.69**	**367.82**	51.74		ABC	**47.61**	**199.43**	**203.72**	59.28
	BCG	**60.65**	54.54	**327.84**	**380.55**		BCG	**45.09**	24.27	**208.90**	**273.88**
	ACG	**53.24**	**415.93**	39.49	**451.08**		ACG	**43.59**	**230.51**	31.96	**249.20**
	ABC	0.0004	**499.51**	**363.22**	**464.89**		ABC	0.0005	**247.14**	**198.67**	**297.66**
	ABCG	**20.46**	**435.16**	**348.00**	**481.00**		ABCG	**17.28**	**235.70**	**246.60**	**231.68**

Table 6. Comparison of both the tactics of MCSVM combined with OCMF.

Tacticts used		CA (%)	RMSE	MAE	T_t ms	T_r ms
OVO	Linear	98.57	0.044	0.014	342.53	343.75
	Polynomial	91.67	0.733	0.209	378.26	380.48
	Sigmoid	39.05	20.99	3.197	395.51	397.73
	RBF	98.98	0.032	0.002	328.53	330.75
OVA		94.76	0.838	0.209	480.00	482.22

Table 7. Comparison of the proposed feature extraction technique with existing one.

Scheme	Data window size	Delay	CA
WT+SVM [15]	>2 cycles	16 samples	95.44
PCA+SVM[19]	>2 cycles	1 cycle	97.30
DF+SVM [22]	<(1/4) cycle	4 samples	95.96
Proposed	**<(1/4) cycle**	**<(1/2) cycle**	98.98

Although the aim of this work is feature extraction technique for quick and reliable detection and classification of transmission line faults. Table 5 shows the extracted fault features at two different fault locations of 40 km and 100 km, respectively. These features could be used in regression algorithms like support vector regression (SVR), multilayer perceptron, decision tree regressor (DTR) etc. to estimate the fault location as well.

With an eye to affirm the eminence of the MCSVM, the suggested feature extraction technique is also validated by combining it with other ML-based techniques such as ANN and kNN. The obtained results in terms of the classification accuracy (CA), root mean squared error (RMSE), mean absolute error (MAE), T_t and T_r are depicted in Table 8. Though the proposed technique has large training time than ANN and kNN, the CA obtained with proposed technique is ≈ 99 % which is higher as compared to others. Hence proved the eminence of the MCSVM.

Table 8. Comparison of the proposed feature extraction technique with other ML-techniques.

Scheme	CA (%)	RMSE	MAE	T_t ms	T_r ms
OCMF+ANN	94.84	0.1015	0.0103	60.408	62.631
OCMF+kNN	97.62	0.1190	0.0476	25.964	30.187
OCMF+MCSVM	**98.98**	**0.032**	**0.002**	**328.53**	**330.75**

4.3. Application to real-field signals

In this subsection, in order to weigh its performance, the proposed technique is applied to the real-time fault events recorded during the different fault types on different phases of different transmission lines in the Maharashtra State Electricity Transmission Network. All the fault signals are in COMTRADE format and recorded at a 1200 Hz sampling rate (24 samples/cycle). More than 100 fault cases are studied. Due to the figure constraints the results are depicted for some cases only (Figure 7) which verifies the applicability of the offered method for real-time fault detection and classification.

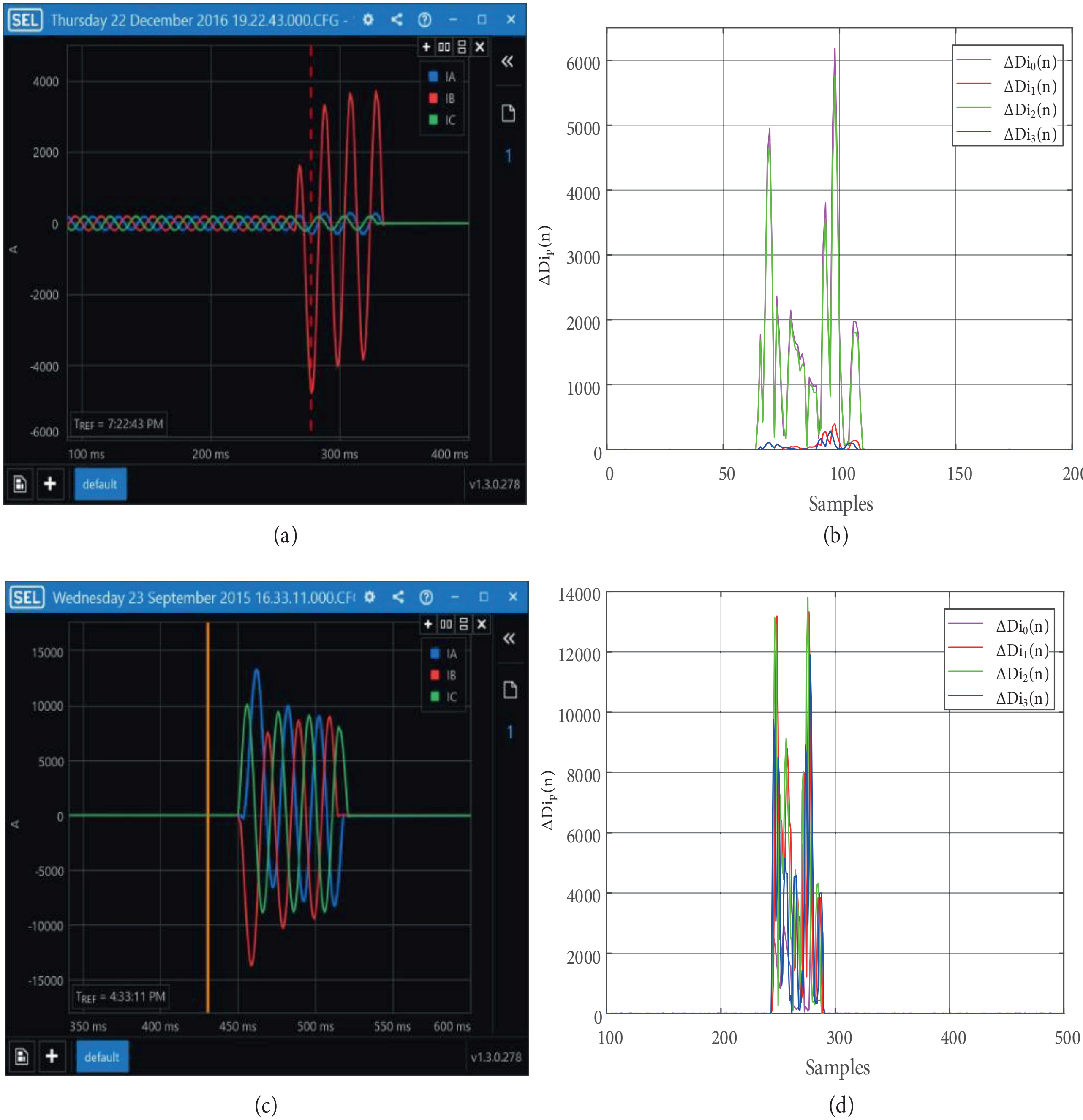

Figure 7. Results for real-field fault events (a) case I: captured fault signal during BG fault on 132 kV Amravati-Ambazari line, (b) extracted ΔDi_p for case I, (c) case II: captured fault signal during ABCG fault on 132 kV Amravati-Achalpur line, (d) extracted ΔDi_p for case II.

5. Discussion

The proposed OCMF-based feature extraction technique excerpts the fault features more reliably in less than a quarter of a cycle with reduced data window size and a minimum delay of as compared to others. Apart from this, the suggested OCMF-MCSVM-based technique, which combines OCMF with supervised ML technique i.e. MCSVM and uses a supervised data, is more competent when used for fault detection and classification as compared to ANN and kNN. The proposed technique exhibits lots of advantages as follows:

- The proposed feature extraction technique involves only addition and subtraction, henceforth has a reduced computational intricacy compared to others and hence offers the promising results without sacrificing the speed.
- Also, it is highly immune to the DDC parameters, noise, and harmonics which are frequently present during a fault.
- Since the proposed method needs only four features for detecting and classifying the faults, the memory requirement and computational time will substantially reduce.
- The proposed OCMF-based feature extraction technique excerpts the fault features more reliably in less than a quarter of a cycle with reduced data window size and a minimum delay of $< 1/4$ cycles compared to others.
- The obtained results proved that when combined with MCSVM, the proposed feature extraction scheme is more efficient to accomplish the speedy and precise fault detection and classification as compared to ANN and kNN.

6. Conclusion

The OCMF-based new, simple real-time feature extraction technique to achieve speedy and precise fault detection and classification on high voltage transmission line is proposed in this paper. The efficacy of the proposed technique to wrench the distinctive fault features is verified in terms of data window size, delay and computational complexity by comparing it with recent techniques. The extracted features are then fed as an input to MCSVM for fault classification. The performance of the suggested OCMF-MCSVM-based approach is verified by simulating several fault events with varying system constraints on 400 kV, 150 km long overhead transmission line. With an eye to justify the potency of MCSVM, the presented feature extraction technique is validated by combining it with ANN and kNN. Also, the proposed technique is applied to detect and classify the real-time fault events at the Maharashtra State Electricity Transmission Network, India. An extensive set of simulation and real-time results has revealed that, the proposed feature extraction technique is highly sensitive to abrupt deviations with reduced data window size, time delay and computational intricacy as it entails much fewer computations compared to others. When combined with MCSVM, the offered technique can be efficiently applied to have speedy and precise fault detection and classification on a high voltage transmission line. The suggested OCMF-MCSVM-based approach merely needs the data from a single end of the line and the decision-making is achieved within a quarter of cycle with an accuracy of ≈ 99 % and hence is suitable for real-time applications.

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