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POWER SYSTEMS AND POWER ELECTRONICS

Detection and classification of short-circuit faults on a transmission line using current signal

Melih COBAN [1, 2*] and Suleyman S. TEZCAN [2]

[1] Bolu Abant Izzet Baysal University, Bolu, Turkey
[2] Gazi University, Ankara, Turkey

Abstract. This study offers two support vector machine (SVM) models for fault detection and fault classification, respectively. Different short-circuit events were generated using a 154 kV transmission line modeled in MATLAB/Simulink software. Discrete wavelet transform (DWT) is performed on the measured single terminal current signals before fault detection stage. Three level wavelet energy values obtained for each of three-phase currents were used as input features for the detector. After fault detection, half cycle (10 ms) of three-phase current signals was recorded by a 20 kHz sampling rate. The recorded currents signals were used as input parameters for the multi-class SVM classifier. The results of the validation tests have demonstrated that quite a reliable fault detection and classification system can be developed using SVM. The faults generated were used for training and testing of SVM classifiers. An SVM-based classification and detection model was fully implemented in MATLAB software. These models were comprehensively tested under different conditions. The effects of the fault impedance, fault inception angle, mother wavelet and fault location were all investigated. Finally, simulation results verified that the study proposed can be used for fault detection and classification on the transmission line.

Key words: transmission line; fault detection; fault classification; support vector machine.

1. INTRODUCTION

Due to the development of technology and the increase in consumption, the demand for electrical energy is increasing worldwide. The fact that electrical energy is easy to access and can be converted to other energy sources quickly and effectively has caused electrical energy to be a coveted energy source. Continuity of electrical energy is of great importance for users these days, when the interest and demand for electrical energy is intense. Unforeseen interruptions due to various reasons can make users aggrieved. One of the main causes of interruptions in electrical power systems is short-circuit faults. Correct reaction to these failures in a short time is of great importance for the reliability of the electrical power system. In order to keep the reliability of the electrical power system high and to minimize the economic losses that may occur due to faults, studies are carried out to determine short-circuit faults in unguarded transmission lines [1].

There are many different studies completed on fault detection (FD), fault classification (FC) and fault location (FL). Most of the studies made generally consists of two stages [2–6]. Firstly, various features are obtained for FD and FC from measured line currents and / or voltage signals, then these properties are evaluated in some rule algorithms, or these features are classified using artificial intelligence algorithms. The biggest problem in the studies has been the issue of how to obtain effective properties for classification from line current and / or line voltage signals [7–9].

Many researchers have studied Fourier transform (FT), wavelet transform (WT), travelling wave, S Transform, Kalman filters and empirical mode decomposition (EMD) for feature extraction [7–13].

FT is a mathematical tool used for analyzing signals in the frequency domain. Every function that can use periodic and finite values consists of the sum of sine or cosine components oscillating at different frequencies. Although DFT is a very important structure for performing the FT of discrete functions, it takes a long time for transformations with a large number of array elements. It is slow for transactions with a large number of data. Instead, the component coefficients are found with FFT (fast Fourier transform). In [7], FFT was used for voltage and current signal preprocessing and feature extraction.

WT is a commonly used feature extraction method for many varieties of FD, FC and FL. Most studies prefer discrete wavelet transform (DWT) instead of continuous wavelet transform (CWT) to decompose the original measured signals so that the features of signals at different frequencies can be detected. Sami presented a method to find a DWT- and SVM-based FC and FL using one cycle current and voltage signals for a 380 kV transmission line [8].

ST is a technique developed from CWT. The calculation outcome of the ST is kept in the S-matrix, while ST contours can be plotted for a two-dimensional visualization and the features can be extracted further. Samantaray performed feature extraction for FC by applying S transform to post fault current signals of a single cycle. Classification success of over 98% was achieved [9].

Hyperbolic S transform is applied to current and voltage signals. The obtained features are provided as input for RBFNN in order to find FC and FL [10].

*e-mail: melihcoban@ibu.edu.tr

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The Kalman filter models its signal as a sum of components consisting of sine and cosine signals. In [11], Kalman filters have been used in feature extraction for FC. The empirical mode decomposition method, which is based on the basic approach that any signal consists of different simple intrinsic mode oscillations, has been used for error classification. After EMD, Hilbert-Huang transform (HHT) is applied to the intrinsic mode functions (IMFs) obtained for instantaneous amplitude, instantaneous phase and instantaneous frequency. Features obtained from HHT are used as inputs for SVM [12]. Also fuzzy logic, WT and neural networks combinations have been used for fault identification [13, 14].

In this study, it is thought that a half-cycle sliding window on three phase current signals will come as a good alternative to detect the short-circuit error with the help of the detail coefficients energy obtained from the 3 level DWT transform without boundary distortions. Figure 1 shows an example, sliding window for a phase fault current and its first level wavelet coefficient. When the fault occurs, a change in the wavelet coefficient is observed. After fault detection, current signals were recorded at half cycle and the samples that were effective in the classification process were selected with the help of neighborhood component analysis (NCA). A short-circuit fault detected by means of the proposed method can be classified within 10 ms. All studies were done in a MATLAB R2018b environment.

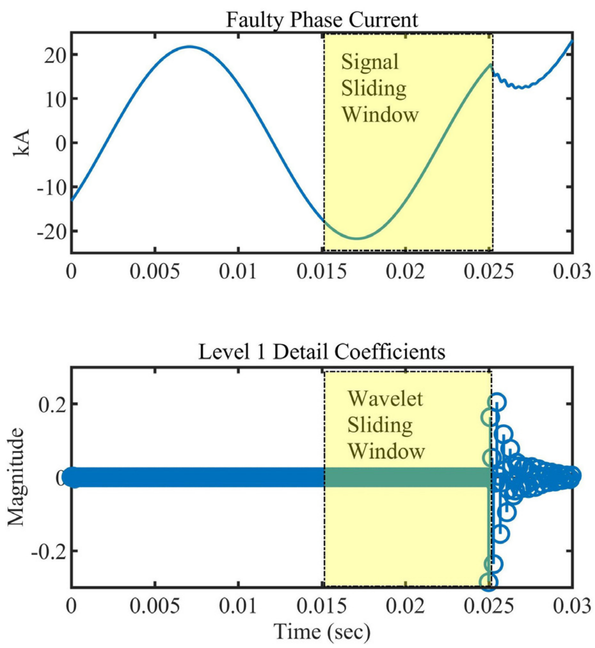

Fig. 1. Sliding window example

The subsequent sections of this paper are organized as follows. Section 2 introduces the basic concepts of the WT, transmission line protection, SVM and NCA. Section 3 in parts 3.1 and 3.2 introduces the fault detection using SVM and fault classification using SVM, respectively. Section 3.3 includes a comparative assessment. Finally, section 4 presents the conclusions drawn from this study.

2. BASIC PRINCIPLES

2.1. Transmission line protection

Short-circuit faults are the types of faults that can cause economic losses in transmission lines. In the event of a short circuit, strong currents can cause overheating and damage power system equipment. Short-circuit faults in power systems are examined under four main headings. The first are single line to ground (SLG) faults. These are faults that occur between any of the phase conductors and the ground. Approximately 80% of short-circuit faults are SLG faults [15]. They may occur as a result of an insulation failure between the conductor and the ground or the conductor falling off to the ground. Secondly, LLG is a short circuit between any two lines and the ground. Approximately 15% of short-circuit faults are LLG faults [15]. Third, LL is a short circuit between any two lines. Approximately 8–10% of short circuit faults are LL faults [15]. LLLG is a short circuit between three lines and the ground. Approximately 2–3% of short-circuit faults are LLL or LLLG faults [15]. These are called symmetrical faults [1].

The transmission lines connect the loads with the generating units located at long distances. Transmission lines are generally protected by distance relays. In conventional systems, distance relays take voltage and current values as inputs and calculate impedance. Primary current and voltage values in the transmission lines are transformed to secondary values by means of measurement transformers. Distance relays use these secondary values as inputs to calculate impedance. To convert primary impedance to secondary one for distance relay, the following formula is used:

$$Z_{\text{sec}} = Z_{\text{prim}} \times \frac{\text{CTR}_{\text{Ratio}}}{\text{VTR}_{\text{Ratio}}}, \tag{1}$$

where Z_{sec} is secondary impedance, Z_{prim} is primary (line) impedance, $\text{CTR}_{\text{Ratio}}$ is the current transformer ratio and $\text{VTR}_{\text{Ratio}}$ is the voltage transformer ratio.

The relay operates according to the calculated impedance value. With the development of technology, digital relays and new techniques have been used. By analyzing the high frequency current and voltage components, FD, FC and FL are made using various methods. Figure 2 presents samples of 4 different types of fault.

2.2. Wavelet transform

WT is a widely used mathematical method for signal preprocessing in a power system. The first study on WT was done by Haar. WT is based on the processing of a simple main wavelet in time domain by adjusting its shifting or width to simulate the original signal. Although CWT is a useful tool, DWT is preferred more frequently as it reduces the calculation requirements. DWT for $f(x)$ is written as [16]:

$$\text{DWT}_{\varphi} f(a,b) = \int_{-\infty}^{\infty} f(x)\varphi_{a,b}(x)\,\mathrm{d}x, \tag{2}$$

where φ is the mother wavelet [17]. DWT method is discussed in this study because they have an affordable processing load. DWT is generally used to provide time-frequency resolution.

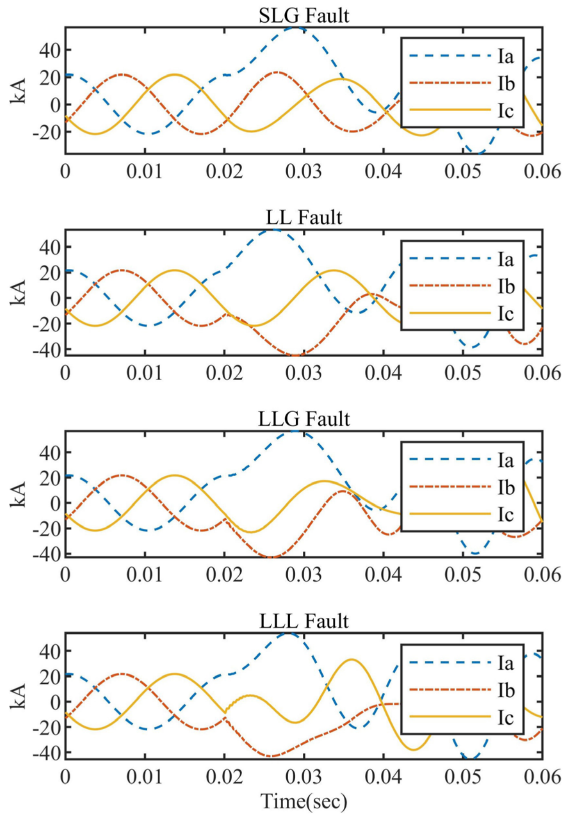

Fig. 2. Examples of fault types

DWT is performed using a filter stack that separates the content of the analyzed signal into low and high frequency components [18]. Approximation and detail coefficients are obtained by down-sampling the signals filtered by low and high frequency filters. Low frequency components of the signal are related to the approximation coefficients. The detail coefficients present the high frequency components of the signal. In DWT applications, where the basic components of power systems are obtained, there are applications where FC is made with the direct use of DWT coefficients. In addition, FL and FC studies are performed using the wavelet coefficient entropy value [19].

In DWT, filter stacks are advanced over approximation coefficients. In this manner, low frequency signals are decomposed into narrower bands in each layer. This causes the DWT coefficients to represent unequal frequency ranges. The DWT block diagram is provided in Fig. 3.

As shown in Fig. 3, the discrete x[n] signal was sampled with sampling signal f_s and applied to the filter stack. The detail ($x_{d1}[k]$) and approximation ($x_{y1}[k]$) coefficients in the first layer were obtained by passing the x[n] signal through the high pass separation filter (HPF) and the low pass separation filter (LPF) in the first layer. These coefficients shared the observable frequency content of the input signal in the range of $(0 - f_s/2)$ as high and low frequency parts. After the first level, the same process is continued over the approximation coefficients and the approximation coefficients at each level are compressed into narrower bands. The DWT, whose first 2 levels are clearly given in Fig. 3, can be advanced as much as the desired n level number by considering the window length. 4-level wavelet decomposition using the db4 mother wavelet is shown in Fig. 4.

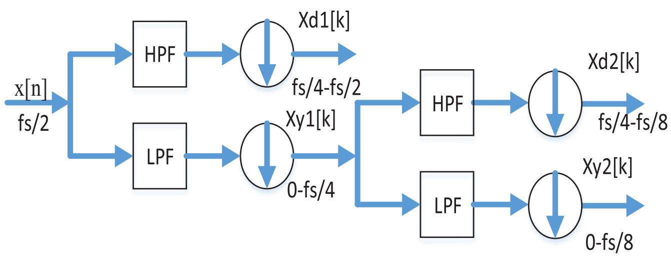

Fig. 3. Wavelet analysis based on [17]

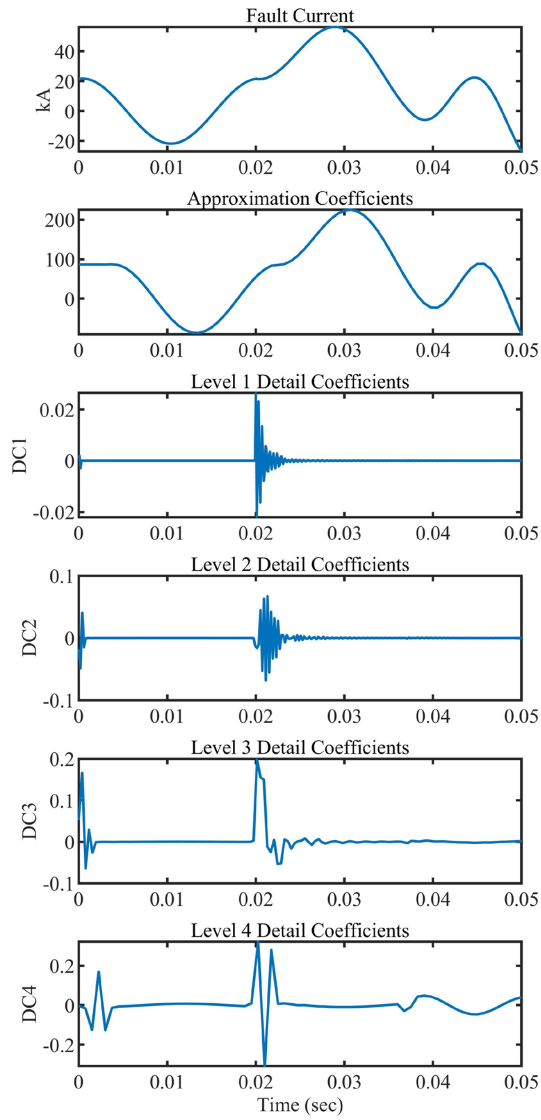

Fig. 4. Example of wavelet decomposition

2.3. Support vector machine

SVM used in the solution of data classification and regression problems was proposed by Vapnik [20]. It has been used successfully in the construction of smart machines, pattern recognition problems and prediction problems. In the classification process using SVM, there are mainly training and test data.

SVM can overcome classification problems with large feature space. It is also claimed that SVM-based classifiers show better performance than traditional ones [19].

SVM, the first to solve binary classification problems, is designed. However, most of the real applications require multi-class SVMs. For example, since there are many disturbances in FC in power systems, multi-class SVMs make it different from healthy conditions. For this reason, methods that can classify more than two data sets, called multi-class SVM, have been proposed in recent years. The most widely used multiple classification methods are one-against-one (OAO) and one-against-rest (OAR) methods [21]. In multi-class SVM, since SVM will work with two classifications, before multi-class classification, the labels of the data are converted into a form suitable for binary classification. Therefore, the data is encrypted before classification, and after classification, the data is transformed into an appropriate class tag by decrypting the class tag.

In the OAO method, each machine is trained by taking a single class against one class. If there are k number of classes, $k(k-1)/2$ classifiers are constructed. In Fig. 5(a), the structure of the OAO multiple classification method is given. The OAR method, on the other hand, is an old and common method used in the multiple classifications method. In this method, if there are k classes, k binary classifiers are created [22]. Also each sample set is trained by assuming that all remaining samples belong to a set, and k training operations are performed in the case of k classes. I. takes the class data as positively labeled and the others as negative [22]. In the test, the class of the incoming sample is found by comparing the support vectors obtained during the training. In Fig. 5(b), the general structure of the OAR multiple classification method is presented. More comprehensive information on SVM can be obtained from [20].

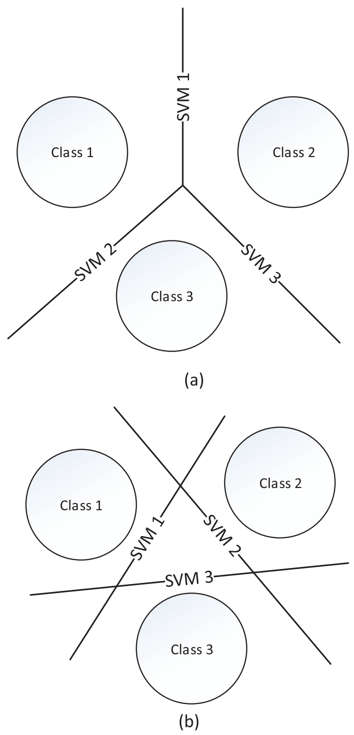

Fig. 5. (a) structure of OAO, (b) structure of OAR based on [21]

2.4. Neighborhood component analysis (NCA)

NCA is used as a feature selection and size reduction technique. In NCA, features are weighted in a way that maximizes the possibility of correct classification. Feature selection is made with the weights obtained. The selection of features in machine learning applications is important for the performance of the model. Therefore, it takes part in NCA classification studies. The NCA uses a set of inputs and associated tags. In NCA, the aim is to find a weight vector that will select the feature subset of the nearest neighbor classification algorithm that optimizes the correct classification probability. The NCA method is calculated from a stochastic variant of the KNN classifier [23].

3. SIMULATION MODEL

In this paper, a real 50 Hz 154 kV transmission line model was studied. The length of the transmission line is 71.3357 km. A distributed line model was used to simulate a transmission line at Matlab / Simulink. Information about the transmission line is given in Table 1. In the transmission line shown in Fig. 6, measurements are made from the bus S.

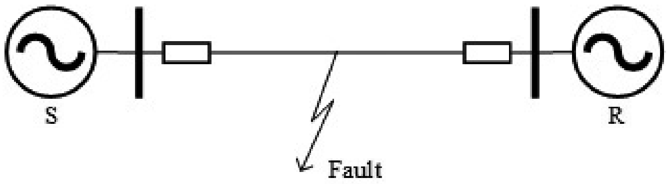

Fig. 6. Transmission line model

Table 1
Transmission line parameters [24]

Parameter	Positive sequence	Zero sequence
R (Ohms/km)	0.12046	0.14231
C (H/km)	8.5138×10^{-9}	6.1677×10^{-9}
L (F/km)	1.3977×10^{-3}	2.2224×10^{-3}

The Matlab / Simulink model is illustrated in Fig. 7. The three-phase fault block presented in Fig. 7 is used to perform a short-circuit fault in the transmission line. By means of this block, ground resistance, fault resistance and fault inception time can be determined.

3.1. Fault detection using SVM

Organization of the FD system is displayed in Fig. 8. The success of the FD system depends on the suitability of the input data used to solve the problem. Different frequency components in a signal indicate the properties of the signals [25]. Three phase current measurements taken from point S are applied as input in the system. DWT is applied to current signals to extract features in the current signals. The FD system is trained with the recorded faulted and no-fault data. After the training, this allows to determine the stage at which the fault occurred.

In this study, a db4 mother wavelet has been used to obtain input features. Mother wavelet selection has been studied by researchers [25–29]. Previous studies have shown that the db4

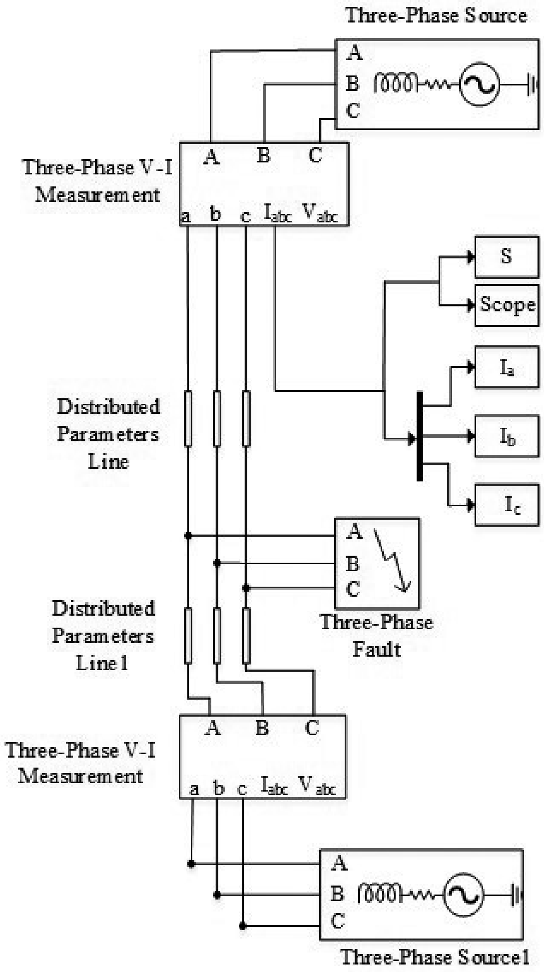

Fig. 7. Matlab / Simulink model

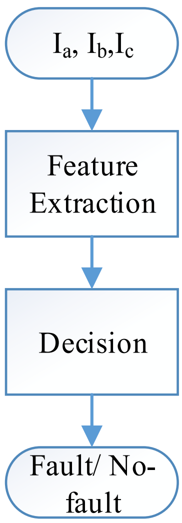

Fig. 8. Fault detection diagram

mother wavelet is a good option for determining FD, FC and FL at preprocessing of measured signals with WT [27, 28]. In addition, db6 and db8 mother wavelets were tested and the results were shared in order to minimize the response time in FD.

The DWT was performed at three levels. The energy of the obtained detail coefficients (C_1, C_2, C_3) was calculated using equation (3).

$$E_i = \sum_{j=1}^{N} \left|C_{ij}\right|^2, \quad i = 1, 2, 3. \tag{3}$$

Here, N is the number of samples in the window and C is the wavelet coefficients. Figure 9 shows the current (I_a), C_1, C_2, C_3 and the energies of the detail coefficients (E_1, E_2, E_3) measured in phase A, when a fault occurred at 0.025 ms. Three-phase current (I_a, I_b, I_c) has been sampled at 20 kHz and 200 samples (10 ms) were recorded for performing DWT. In order to operate DWT, the wavelet toolbox in Matlab was used.

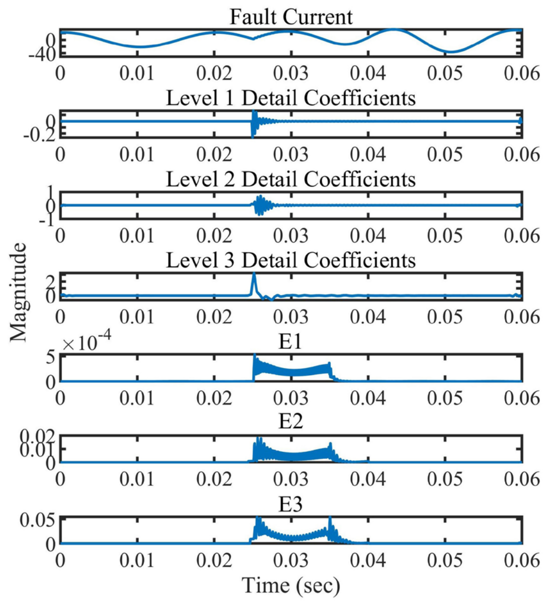

Fig. 9. Current, wavelet coefficients and wavelet energies

For the FD problem, studies have been executed on the model transmission line shown in Fig. 7. Matlab Simulink has been used to generate signals to be used in FD. Current signals obtained during different types of faults (AG, BG, CG, AB, AC, BC, ABG, ACG, BCG, ABC) are stored. Sample frequency is 20 kHz. 9 features were recorded, 3 from features of each phase current wavelet coefficient energy value. A total of 500 simulation studies were carried out, with 250 faulted and 250 non-faulted. In the cases where faults occur, 10 different fault types have been selected to be equally divided. The faults were generated using different fault impedance between 1 to 100 ohms and an inception angle between 30° and 330°.

The SVM-based FD system was trained by using a training database whose size is 9×500. In order to confirm the operation of the fault detector, simulations were executed comprehensively by various types of faults in the transmission line. The detection results are summarized in Table 2. According to the results obtained, nearly all faults and no-fault cases have been correctly detected. The lowest accuracy has been noticed in detection of the LLG faults, at 97%. However, overall detection accuracy remained at 98.5%.

Table 2
SVM-based detection results

	Type of faults	True p	False prediction	Performance (%)
Fault	AG	100	0	100
	BC	96	4	96
	ABG	97	3	97
	ABC	98	2	98
No-fault	AG	100	0	100
	BC	100	0	100
	ABG	98	2	98
	ABC	99	1	99
Total		788	12	%98.5

An SVM-based detection system outputs 1 when failure is detected and 0 when there is no failure. The Gaussian function has been chosen as the kernel function for SVM. The multi-class method is OAO. Figure 10 shows the three phase current signals, the wavelet coefficient energies obtained from I_a and the output value of the detection system. In Fig. 10, a fault was generated at 0.025 sec. The proposed system detected the fault at 0.0252 sec. Response time for the proposed system is observed at 0.002 sec. Tests were performed with db4, db6 and db8 mother wavelets in order to see the effect of the mother wavelet on the performance of the FD system. In the tests performed with the db8 mother wavelet, the response time increased and the average became 0.0056 seconds. In addition, the average response time in tests with the db6 mother wavelet was 0.003 seconds.

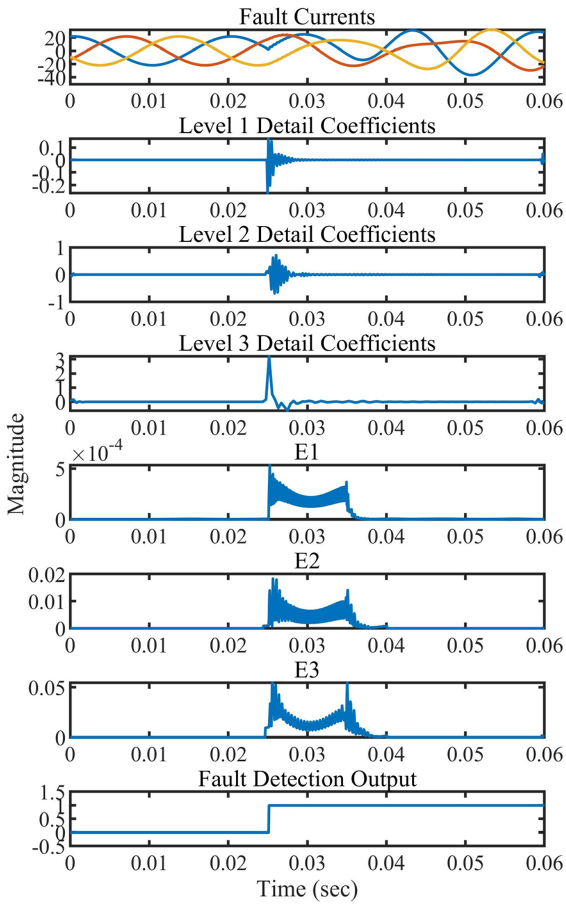

Fig. 10. Operation of fault detection system

In order to examine the effect of fault impedance on the fault detector system, tests were executed with faults on different fault impedances between 0.1 to 150 ohms. As a result of the tests performed, it was noticed that fault impedance did not affect the performance of the fault detector. Also, faults were made at different inception angles and different locations, and it was observed that performance was not affected.

3.2. Fault classification using SVM

The purpose of this section is to find out which line or lines are faulty by correctly classifying the detected fault. For this purpose, current patterns after fault detection were set as input for the SVM classifier. An FC diagram is presented in Fig. 11.

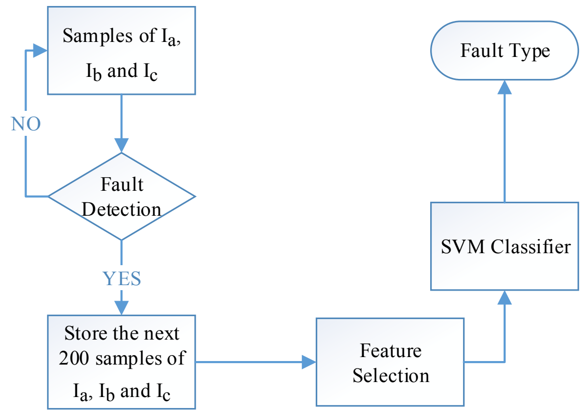

Fig. 11. Fault classification structure

Three-phase current signals have been obtained with a sampling rate of 20 kHz. For FC, a half cycle of post fault is considered. A total of 600 samples have been recorded, 200 samples for each phase current. Ten fault types such as AG, BG, …, ABC have been simulated for generating the training data set. While creating the training data set, different fault location, fault inception angle and fault impedance are used for each fault type. 1920 faults have been performed on the modeled transmission line.

In this study, NCA is used as the feature selection algorithm. As a result of weighting the features with the help of NCA, the SVM input matrix of 600×1920 has been changed as 62×1920. The weights of the features in the FC are observed in Fig. 12.

Dimension reduction may be required to make data sets with a large number of features suitable for analysis and to produce simpler and more meaningful models from the data. Dimension reduction, in the simplest terms, is the process of reducing the number of dimensions with as little loss as possible from the information carried by the original data. Feature selection can be defined as the selection of a sub-feature set that best represents the data set.

Feature selection performs the dimension reduction process by removing the less important features from the data set in the representation of the data [23].

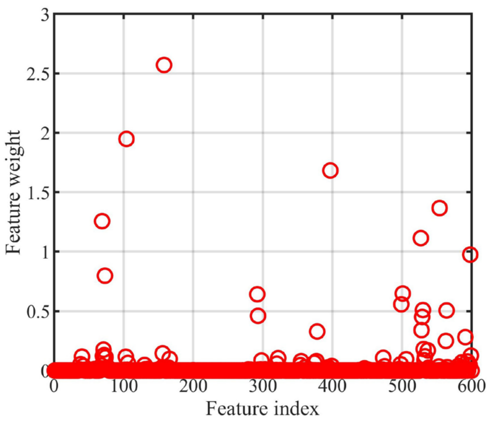

Fig. 12. Weights of features

The Gaussian function was chosen as the kernel function for SVM. The multi-class method is OAO. Two tests were applied to examine the performance of the multi-class SVM (MCSVM) classifier. The first of these is the 5-fold cross-validation test. In this test, the training data set has been randomly divided into 5 different groups. In order to test each group separately, 1 group has been selected for the test and the remaining 4 groups have been trained. Afterwards, the average accuracy rate has been calculated. The results obtained are presented in Table 3. For the second test, in order to examine the performance of the MCSVM-based classification model, it has been tested using samples that had not been included in the training data. Table 4 presents the second test results.

Table 3
5-fold cross validation result

	Training	Testing	Performance (%)
SVM-1	62×1536	62×384	100
SVM-2	62×1536	62×384	99.68
SVM-3	62×1536	62×384	100
SVM-4	62×1536	62×384	99.21
SVM-5	62×1536	62×384	100

Table 4
SVM-based classification results

Fault type	True prediction	False prediction	Performance (%)
AG	100	0	100
BG	99	1	99
CG	100	0	100
AB	98	2	98
AC	100	0	100
BC	99	1	99
ABG	100	0	100
ACG	100	0	100
BCG	98	2	98
ABC	100	0	100
Total	994	6	%99.4

Tests on the FC model were performed to investigate the effect of fault impedance, fault location and fault inception angle that are different from the training data set. Fault impedances were chosen at values of 1, 5, 50 and 150 ohms. The fault inception angle is selected as 35°, 70°, 140° and 220°. Fault location at different values between from 0 to 71.3357 km were taken randomly.

The results obtained show that the fault angle and fault impedance do not affect the performance of the MCSVM classifier. In the FC, between 0–10 km and 60–71.3357 km, it was observed that more misclassification was made as compared to the other part of the transmission line. In the tests performed on the transmission line, FC was made with an accuracy of minimum 96.2% and maximum 99.94%.

3.3. Comparative assessment

The proposed FC system has been compared with the other methods presented in [30–32]. It has been determined that the proposed method is extremely competitive and almost shows better classification accuracy than other compared methods. Information about the compared methods is presented in the Table 5.

Table 5
Comparison of the proposed method with other methods

References	[30]	[31]	[32]	Proposed method
Length (km)	100	150	300	71.3
Frequency (Hz)	60	50	50	50
Voltage (kV)	230	400	400	154
Sampling ratio (kHz)	3.6	1200	5	20
Window size	(1) cycle	(1/4) cycle	(1/2) cycle	(1/2) cycle
Method	SW-ELM	OCMF-MCSVM	WT-ChNN	NCA-MCSVM
Predicted fault class	10	11	10	10
Classification accuracy (%)	**98.3**	**98.98**	**98.73**	**99.4**

The compared methods and the proposed method have been tested for different fault resistances, fault distances, fault inception angles and fault types, and their classification accuracies have been verified as a result of tests.

Since the SW-ELM (summation wavelet extreme learning machine) method uses 1 full cycle [30], it has the longest response time. Although the OCMF (open circuit medium filter) MCSVM method has the shortest response time [31], it requires a large data storage area due to its very high sampling rate (1200 kHz).

Although the proposed method and WT-ChNN (Chebyshev neural network) have the same response time [32], the classification accuracy is 99.4% and higher than the others. Therefore, the proposed method has been proved of particular value. Considering the response time and classification accuracy together, it was observed that the proposed system can be a lucrative choice. Also, to the best of our knowledge, this is first attempt at a combination of NCA-MCSVM for short-circuit fault classification in a transmission line.

4. CONCLUSIONS

This paper presented SVM-based methods for fault detection and classification using measured single terminal current signals in transmission lines. Real transmission line parameters were used for developing and testing the study. The FD and FC system showed efficient performance for a large number of different fault cases. After an extensive series of tests, the db4 mother wavelet was considered the best one in terms of accuracy, considering different states such as fault impedances, fault inception angles and fault locations for FD. As discussed in previous sections, the proposed method can be implemented easily as it uses a lower sampling rate with current signals. From the results obtained, it is clear that the proposed detection and classification system is stable as to the fault type, fault impedance and fault inception angle. In the test cases, the FD error was less than 1.5%. FC average accuracy was found at 99.4% for 10 fault types. Another advantage of the study that should be highlighted, since it uses current measurements from a single terminal, is that it does not require synchronization from the other end of the transmission line for communication and measurement.

This study can been expanded further in order to verify the robustness of the proposed method on open circuit faults and switching faults and to consider how to implement the proposed method in more complex topologies.

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