Short Circuit Fault Classification and Location in Transmission Lines Using A Combination of Wavelet Transform and Support Vector Machines

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Abstract: In this paper, a modern synthetic framework which has the capability to rapidly Classify and locate short circuit faults over transmission lines is presented. The proposed algorithm singles out short circuit faults based on the measured voltage waveform and three-phase current when fault events occur in power transmission lines. The values resulting from the three-phase currents and the three-phase voltages wavelet transform are used to fault classification algorithm. Then, fault location algorithm is activated as the result of fault classification. Different kinds of methods such as multilevel wavelet transform and support vector machine have been combined in a set to determine fault classification and location at every time. This paper lays out the fundamental concept of the proposed framework and introduces a pattern recognition approach via wavelet transform, statistical processing techniques, neural network (NN) and a joint decision-making mechanism. Voltage and the recorded current values in measurement devices from the fault moment to a quarter of post-fault have been used for preprocessing and training in the support vectors machines.

1. Introduction

During the last 50 years, electric power system has rapidly developed and grown, the issue which itself has resulted in increased operation lines in number and length. Power quality in transmission lines today is focused on as an important factor to continuously access electrical services from the power stations (power supply facilities) to the consumers (end users).This matter has set forth transmission lines as one of the key elements of power system since power transmission lines like all the other equipment of power system are exposed to different types of fault. Fault occurrence in transmission lines is of unfavourable & inevitable power system phenomena having harmful effects on the network [1-11].The most common fault type on power transmission lines is short circuits generated due to various. Thus after short circuit occurrence & power outage by protection relays, the problem of line restoration service (continuity of service) is raised. Because power transmission lines have been extended on long routes, in order to locate fault in case of using inspection procedure, lots of time will be required; though the transmission lines are long and cross areas such as uneven mountainous regions or maybe inspection or search happen under some adverse climatic conditions when mainly lines faults occur that accompanies many problems for the repairs team. In some cases even long time inspection doesn't lead to fault locating since many of the faults occurring in suspension insulator aren't readily visible. Thus utilizing some methods or using some devices able to determine fault location quickly & accurately enough seems necessary. These devices are called fault distance detector or the algorithms used in them are termed fault locating algorithms. Recently, artificial neural networks (ANNs) have gained some success in power system applications. There are lots of advantages in ANNs like very good security against noise, but their building exposed to real-world (practical) conditions is used less compared with the conventional methods [2].Several algorithms have been reported for fault detection, classification & location in transmission lines separately. Methods are distinguished regarding the selected

model for transmission line or phasor type (voltage or current phasor) used. The methods using time dependent differential equations solution related to transmission line are the most applied ones in the articles[3-4]. There are lots of articles that benefitted from other methods like wavelet transform, neural networks [5-6] or travelling waves [7] for fault location. In this paper, a novel method has been used for short circuit fault classification and location in transmission lines by model pre-processing & the results analysis from the study system, fault inception angle (FIA) has no effect on NN training process. In simulation, MATLAB & PSCAD/EMTDC programs have been employed & fault data sample has been created regarding extensive changes on fault location, resistance & type. In this study, a hybrid set has been presented including voltage waveforms via discrete wavelet transform and three-phase current analysis, a set of support vector machines & support vectors regression for fault classification & location. Efficiency and results obtained in this study is compared with another study which is based on Multilayer perceptron (MLP).

2. The proposed Algorithms

A. Wavelet Transform

Compared with Fourier transform, wavelet transform has this efficiency and advantage that besides stating how much of each frequency presents in the waveform, it shows when theses frequencies appear in the waveform. In fact, it contains two dimensions of time and frequency. Wavelet transform is virtually a more general state of Fourier transform. Applying Fourier transform is appropriate for the waveforms stationary over time. But the signals which are not stationary over time and lack iterative property rather they are transient waveforms occurring several times in a cycle belonging to non- stationary signals class and therefore, Fourier transform can't use these signals to isolate frequency-time specifications, in such cases a transform should be applied that has time factor along with frequency the quality that wavelet transform has [11].

Continuous wavelet transform for signal X(t) taking mother wavelet Ψ (t) is defined as the following:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \Psi\left(\frac{t-b}{a}\right) dt \qquad (1)$$

Where a & b stand for scaling and translation parameters, respectively. By relation (1), it can be inferenced that wavelet coefficients (CWT (a, b) give a measure of similarity between the scaled & shifted wavelets (basis functions) with signal x(t).

Discrete wavelet transform for X(t) signal can be defined as the following:

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} x(k) \Psi\left(\frac{n-kb_0 a_0^m}{a_0^m}\right) \qquad (2)$$

In DWT, some filters with various interruptions frequency are used for signal analysis in different signals by the signal passing high-pass & low-pass filters, its diverse frequencies are analyzed. In DWT, signal resolution varies by control & scale filters functions through down sampling & up sampling. Typically, this changing trend on a dyadic network is done by $a_0=2$, $b_0=1$. Therefore, the corresponding scales and time shifts are respectively as $a_0=2^m$, $b_0=k2^m$. Considering the above explanations after a pre-processing, it is possible to achieve some good and remarkable properties of wavelet transform partial components and then to apply them in support vector machines training.

B. Support Vector Machine

Support Vector Machine (SVM) is a new kind of learning machine and is considered of supervisor learning kinds. SVM was introduced by Vapnik in 1992 and has been established based on statistical learning theory [8-9]. Support vector machine is widely employed for clas-

sification, regression and estimation of density. Support vector machine separators create linear boundaries in input space. Via expanding input space into a bigger one, it is always possible to increase freedom degree using basic functions similar to polynomials, MLP and RBF networks. Generally speaking, returning the primary input space with non-linear boundaries and transmitting it to the new input space (the expanded) with linear boundaries, it is viable to state that the idea is a support vector machine including two processes as the following:

- Input vector non-linear mapping into a feature space with higher dimensions is hidden from input and output perspective.
- Creating an optimal plate for separating the features gained in a process.

The first process basis is Cover theory about the patterns separability. Suppose that the input space consists of a set of inseparable patterns, Cover theory explains that by transmitting the mentioned patterns to a new feature space, we can obtain the features having high potential to be linearly separated on the condition that;

- Mapping is non-linear.
- The feature space dimensions are sufficiently high.

The first process guarantees the two above mentioned conditions. Note that Cover theory doesn't describe the separating plate optimization rather the plane optimization process is dealt with in the second process. In this state, the separating plate is defined as a linear function from the mapped vectors in feature space instead of the main vectors in input space; thus in the state that the basic functions are specified, to design the boundaries in the expanded space is easier and the freedom degree is higher than that of designing in input space.
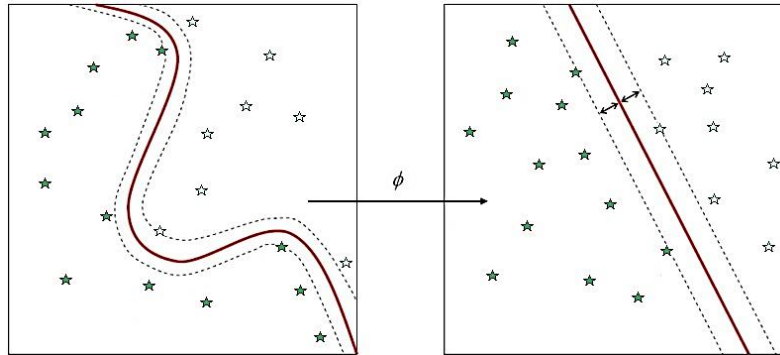

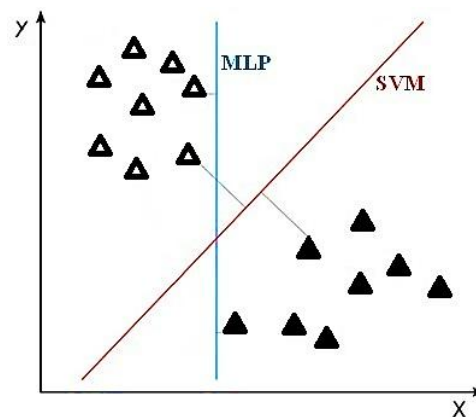Figure 1. Input space and Feature space

Figure 2. Support Vector Machines are very useful and effective in classification and regression

The most important advantage behind this method is covering Structure Risk Minimization (SRM) against Empirical Risk Minimization (ERM) used in neural networks. SRM is to minimizing generalized upper boundary .While in ERM, only training error drops. It has been proved that support vector machines are very useful and effective in classification and regression.

Figure3 depicts support vector machine. Kernel functions used conventionally in SVM are polynomial function of p degree, radial basis function & sigmoid function (perceptron) should meet Mercer theory.

In SVM of radial basis function (RBF) type, the number of radial basis functions &their centers are automatically determined by support vectors number and their values, respectively. In SVM of two layer (bilayer) perceptron kind, the number of hidden neurons & their weight vectors are automatically determined by support vectors and their values, respectively.
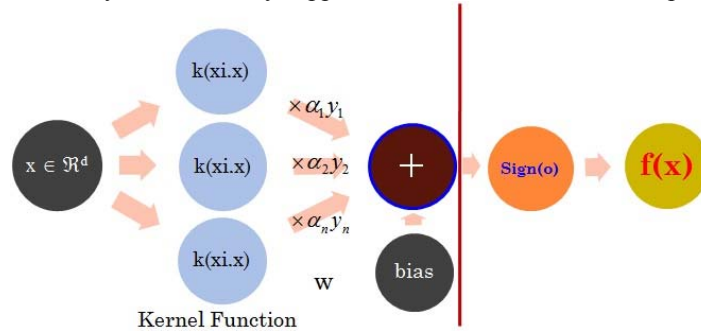

Figure 3. Support Vector Machine Structure for Classification [11].

3. The Proposed Model Structure

In this section, the proposed theory for fault classification and location from structural and systematic perspectives is introduced.
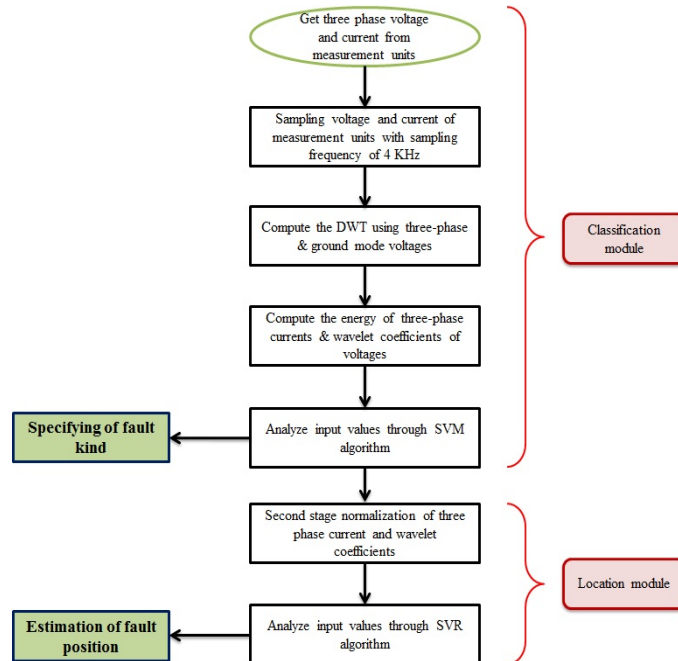
A. The proposed Combined (Hybrid) Set

Figure 4. The proposed hybrid framework for protection system.

In this paper, the fundamental frequency of 60 Hz has been considered for power system designed in PSCAD/EMTDC software. A sampling rate of 20 KHz (333 samples/ cycle are measured by power measurement units) has been chosen for signals extraction from transmission lines. Measurement units are installed in only one bus to achieve three-phase current & voltage signals. Then the acquired data are transmitted to MATLAB program for fault classification and location algorithms analysis. The proposed set, as Figure 4 shows, includes two stages: fault classification and fault location.

This structure can analyze the faults occurring between the two buses equipped with measurement units. Wavelet transform method has been used to extract excellent features, from three-phase voltage signals, as a reliable indicator in fault classification.

The first stage of Hybrid Set, when a fault is detected, 1st level discrete wavelet transform is applied to three-phase voltage signals for one cycle after fault occurrence. The features of signals are achieved by computing the energy of the currents &the voltage waveforms wavelet detail coefficients. Then the obtained features are used as SVM input to detect faults kind occurred in power system. In the end, after fault kind determination, fault location module including SVR receives the new inputs resulting from the second normalization stage & performs fault location task.

B. The Proposed Power System Model

The studied model in this work is a two-machine three-phase 400KV power system simulated for transmission line fault classification and location. We investigate single circuit transmission line with 100 Km length in this paper. The study system single line diagram has been shown in Figure 5 and its parameters have been pointed out in table 5. The sources No.1 & 2 are the same size, δ (phase difference between source 1 & source 2) equals 30 degrees, with source 1 leading.
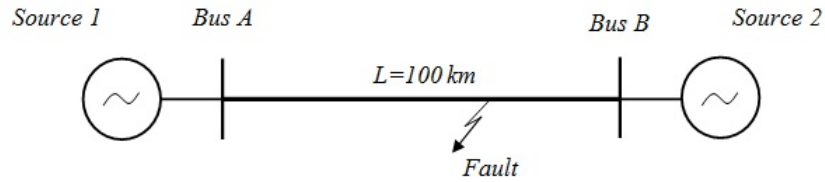

Figure 5. Simulated Power System Model.

4. The Proposed Algorithm Combined Framework

As Figure 4 illustrates, the framework consists of two modules for fault classification and location .The designing details for each module are expressed in the following, respectively.

A. Fault Classification Model

In this section, the proposed method for fault classification is explained using discrete wavelet transform & SVM binary classifier.

In this paper, discrete wavelet transform is used for extracting the hidden information in the voltage waveforms when a fault has occurred in transmission lines that then changes appropriately for fault effect and fault features extraction. Choosing mother wavelet is very important in detecting & locating different types of transient faults. Typically, the appropriate mother wavelet utilized for protection applications is Daubechies (db) wavelet. Mother wavelet db4 having higher accuracy compared with the other wavelets has been run as a finite impulse response high-pass filter.

The SVM classifier has to be trained by using different fault scenarios in a certain power system. Then the other fault scenarios are employed for the proposed algorithm performance evaluation.

In this paper, normalized wavelet energy of the post-fault voltage and normalized energy of the post-fault current are used as the input to SVM classifier. The general method to obtain input features using discrete wavelet transform is described as the following:

- Transient voltages & currents are registered in the designed measurement bus.
- The registered transient voltages & currents are sampled in measurement units, with frequency (67 samples/cycle) $F_S = 4$ kHz in a quarter of cycle after fault occurrence.
- Ground mode Voltages & currents are achieved through the following formula:

$$V_0 = V_R + V_S + V_T \tag{5}$$
$$I_0 = I_R + I_S + I_T \tag{6}$$

- DWT is applied for all three-phase & ground mode voltages to obtain the wavelet coefficients using db4 as the mother wavelet.
- Wavelet transform coefficients in Scale-1 are squared (WTC^2).
- Each signal's wavelet energy is calculated by summing WTC^2 over a quarter of cycle after the fault being detected, (E_k) k = a, b, c, 0.
- The currents energy for a quarter of cycle is calculated after instantaneous fault (I_k) k = R, S, T, 0.
- The calculated wavelet energy of transient voltage and energy of the phase currents are normalized as:

$$E_{N_i} = \frac{E_i}{E_R + E_S + E_T + E_0} \; for \; i = R, S, T \tag{7}$$

$$I_{N_i} = \frac{I_i}{I_R + I_S + I_T + I_0} \; for \; i = R, S, T \tag{8}$$

In order to classify different fault types, 4 SVM dyadic classifiers are used (SVM$_k$) (k=1... 4) and each SVM has been trained to detect whether or not there is any faults in the desired phase. Furthermore, SVMs are organized as mutual unique classifiers. So that SVM$_1$ has been trained to detect fault in phase R, SVM$_2$ has been trained to detect fault in phase S, SVM$_3$ has been trained to detect to fault in phase T & SVM$_4$ has been trained to detect if the fault has been ground or not. The output of every SVM$_i$ (i=1... 4) is either +1 or -1. For the first 3classifiers, +1 means that the fault has occurred in the considered phase & -1 means there is no fault in that considered phase. For the last classifier, +1 indicates that fault is grounded.
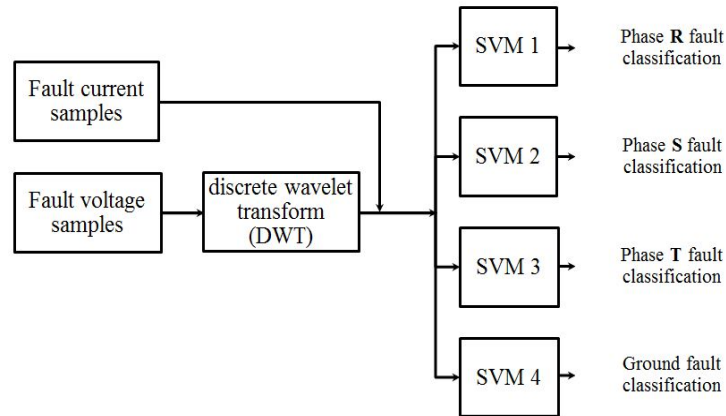

Figure 7. Fault classification structure view.

The training process is carried out to calculate SVs in order to define optimal hyper plane. The input features are the normalized wavelet energy of the three phases & ground mode volt-

ages in addition to the normalized energy of the post-fault three-phase currents. Thus the processed features in the training matrix are stored in dimensions 7×N where each column stands for one feature and each row presents one training sample. The input to every SVM classifier is the training matrix & a class vector pre-labeled (2×N) (it includes class label for each training data).The training process is completed once and SVMs classify fault and then SVMs are prepared for the new input data classification. The algorithm operation schema is shown in Figure 7.

A. Fault Location Model

A set of Support Vector Regressions (SVRs) has been used to estimate fault location. As Figure 8 depicts, after fault type determination using SVMs, the proposed set using SVR is able to determine fault location accurately.
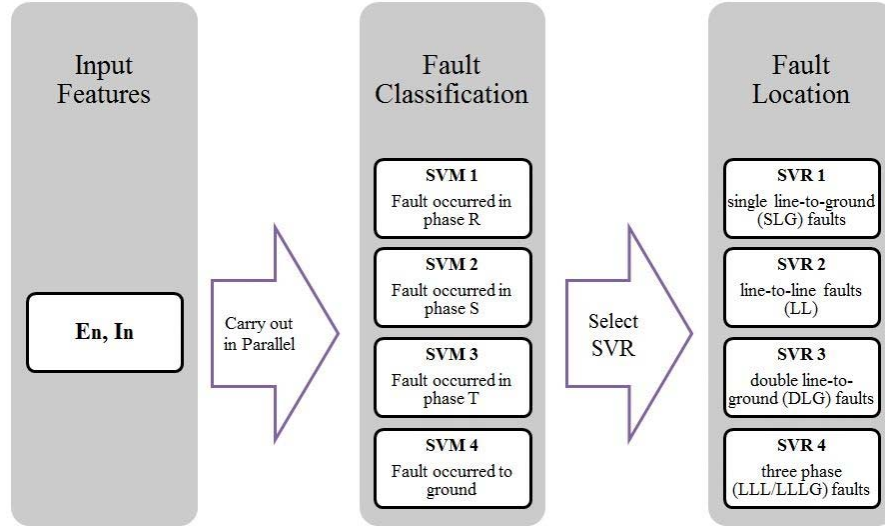

Figure 8. Fault classification & location models structure.

The training process in SVR accompanies in order to estimate fault location by generalizing the input features applied in the classifier SVM training process. As mentioned in the previous section, the input features applied in the SVM classifier training process are the normalized wavelet energy of the three phases & ground mode voltages in addition to the normalized energy of the post-fault three-phase currents. In the training process of SVR, the training samples are the normalized wavelet energy of three-phase voltages in addition to the normalized energy of the post-fault three-phase currents (input features) & their corresponding fault location. Now in order to minimize numerical problems risk, the second normalization is done as the following equation [10, 11]:

$$\tilde{x}_i = \frac{(x_i - \mu_i)}{\sigma_i} \tag{9}$$

Where $\tilde{x}_i$ is the normalized feature value, μ_i and σ_i are the mean and standard deviation based on all of the training samples of the ith feature and the samples number is 6. This normalization decreases the risk that feature components with large dynamic range dominate those having smaller ranges [10]. The training samples & the fault location corresponding to them are first obtained through computer-based simulated power system measurement units, which after processing are stored in a training matrix in the dimensions 7×N.

5. Simulation Results

The proposed hybrid algorithm has been run on two-machine system model. Gaussian RBF Kernel has been used for training and testing the SVM classifier. Different fault scenarios have been simulated in the system under the fault resistance extensive variations (R_f) and fault location (L). The following values have been utilized in this study:

- Fault distance: $0 \leq L \leq 100$km with $\Delta L=5$km, that means faults are different in 21 locations.
- Fault resistance: $0 \leq R_f \leq 80$ Ω with $\Delta L=5$ Ω, that means 17 different fault resistances for each fault.

For the aforementioned scenario, all the 11 single line-to-ground (SLG), line-to-line (LL), double line-to-ground (DLG), three phase (LLL/LLLG) faults (RG, SG… RST, RSTG) in the four algorithms have been considered. Regarding the fault resistance number R_f, 17 scenarios &the locations under the influence of fault are 21, thus 357 training samples have been created for each one of the 11 fault types. Voltages & currents in Bus 1 have been registered with a sampling frequency f_s = 20 kHz. Wavelet transform & SVM in program MATLAB have been used for data processing. At the end, the result of this experiment is compared with a similar study in which MLP is used instead of support vector machine with Gaussian RBF kernel.

A. Classifier Algorithm

Using a down sampling, 197 samples have been chosen randomly & have been used as the training data set for support vector machines classifier. In the following, the algorithm has been tested using the remaining data set (66 samples) the graphic results of the training & test samples for all of the 4 SVMs are illustrated in Figure 9.

The classifier algorithm accuracy is determined by the following relation:

$$\%accuracy = \frac{Number of correct fault type classified}{Number of test cases} \times 100 \tag{10}$$

Test results for fault classification are given in Table 2. As observed from Table 2, the accuracy of the proposed method is quite satisfactory for fault classification. The overall accuracy for fault classification is 99.62%. This result is compared with the result obtained in a similar study in which the type of NN is different. Where the similar study for fault classification have used the combined WT-MLP and The overall accuracy for fault classification is 90.61%.
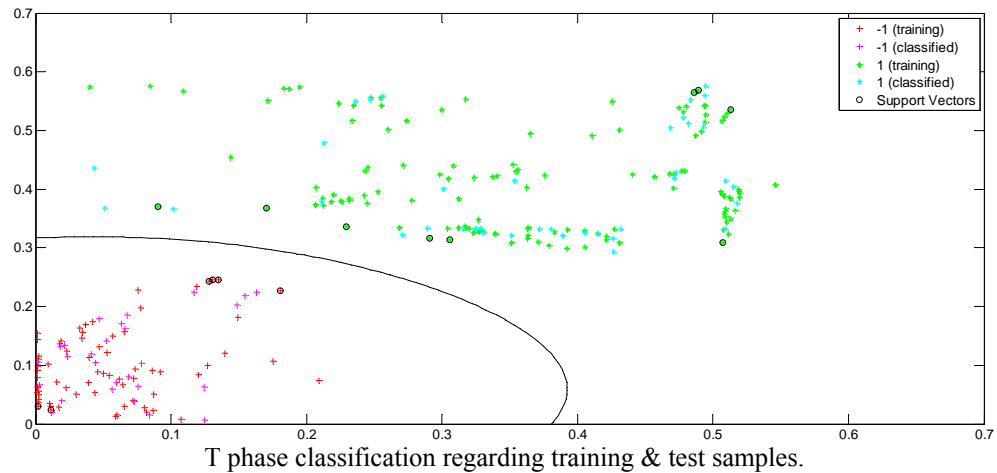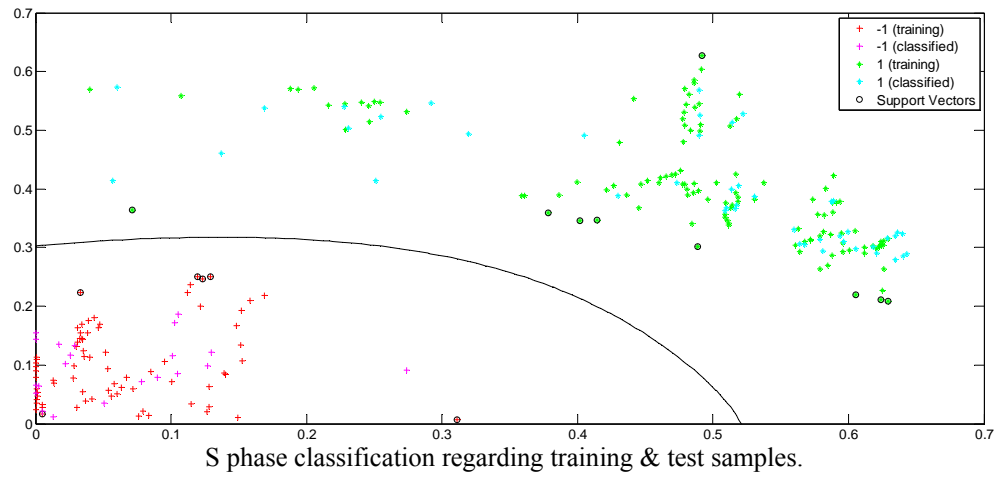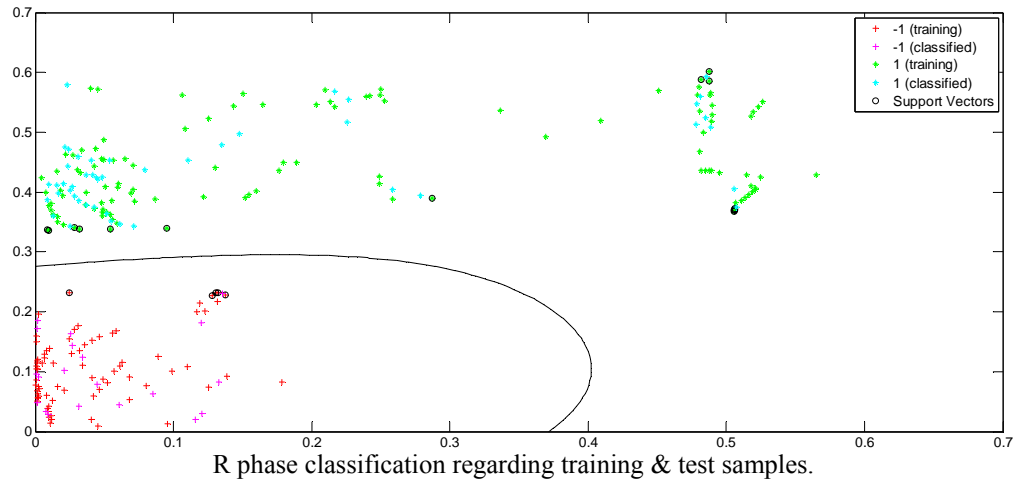
Hence it may be observed that the result obtained using the method proposed in this paper for fault classification is better than the results reported in the similar study used the combined WT-MLP.

Table 2. Efficiency and results obtained in this study is compared with another study which is based on MLP.

Fault type	Samples tested	True fault classifications	No. of misclassifications	WT-SVM accuracy (%)	WT-MLP accuracy (%)
R	66	66	0	100	100
S	66	66	0	100	100
T	66	66	0	100	100
G	66	65	1	98.48	62.42
Total	264	263	1	99.62	90.61

This fault classification is carried out in parallel with the SVM calculations. For example, if the outputs of SVMs are: SVM1=1, SVM2=1, SVM3=0 and SVM4=1, then it is an DLG fault involving phases R and S.

R phase classification regarding training & test samples.

S phase classification regarding training & test samples.

T phase classification regarding training & test samples.
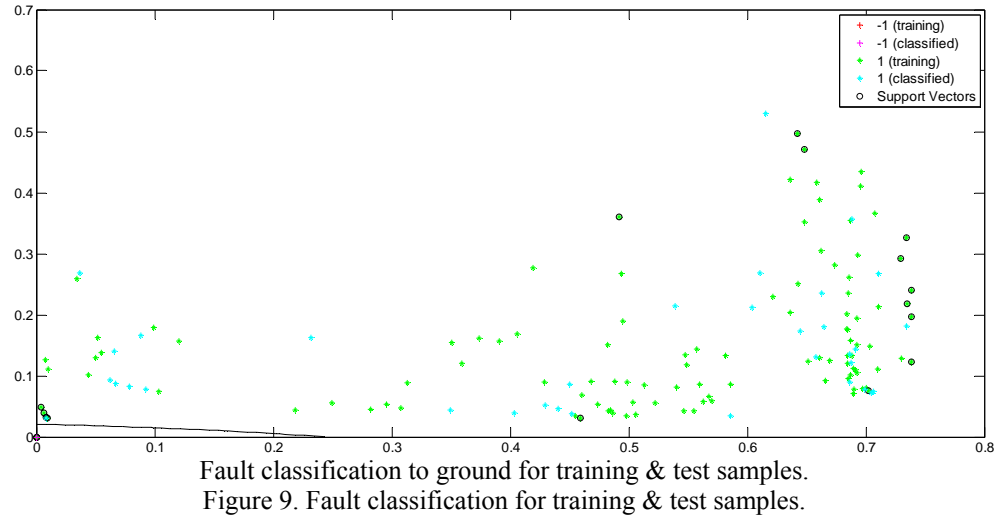
Fault classification to ground for training & test samples.
Figure 9. Fault classification for training & test samples.

B. Locator Algorithm

Using a down sampling, 178 samples have been chosen randomly and use as the training data set for locator algorithm (SVR).In the following, the algorithm has been tested using the remaining data set (179 samples).The graphic results of the training & test samples for SVR locator for the single-phase fault S to ground have been depicted in Figure 10 and Figure 11. The criterion for evaluating the performance of the fault locator is defined as:

$$\%Error = \frac{|Actual faultlocation - SVRoutput|}{Length of the line} \times 100 \tag{11}$$
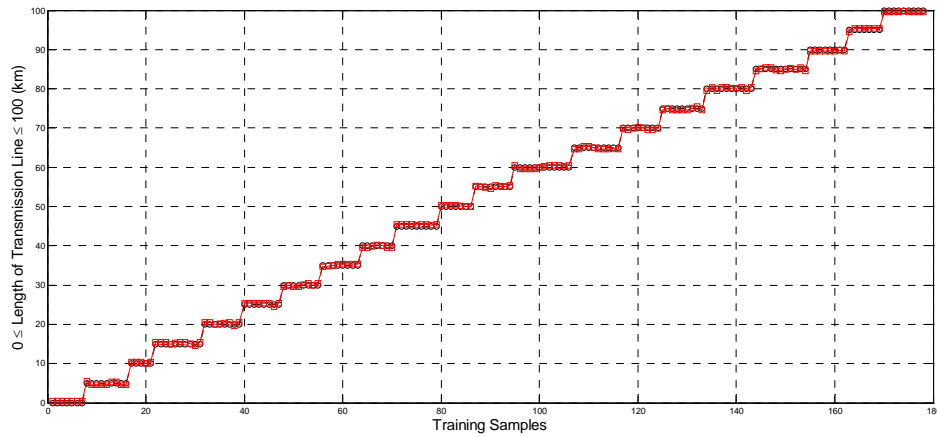

Figure 10. Estimating fault location phase S to ground with respect to the training samples

Table 3. Comparison of fault location error of WT-SVR and WT-MLP.

Type of fault	Min. error		Max. error	
	WT-MLP	WT-SVR	WT-MLP	WT-SVR
LG	8.4819	0.0003	31.8492	0.0027
LL	5.7834	5.3343×10^{-4}	34.5708	8.3236×10^{-4}
LLG	10.4866	0.0015	38.1668	0.0028
LLL/LLLG	10.6752	0.0006	38.4492	0.0018

The minimum and maximum error with WT-SVR and WT-MLP are given in Table 3. From Table 3, it is observed that maximum fault location error with WT-SVR is less than WT-MLP.

In table 4, the results of four fault cases with different location conditions with training zones (outside of test & training samples) have been taken into account.

Table 4. Locator algorithm performance result for all the four experimental fault samples

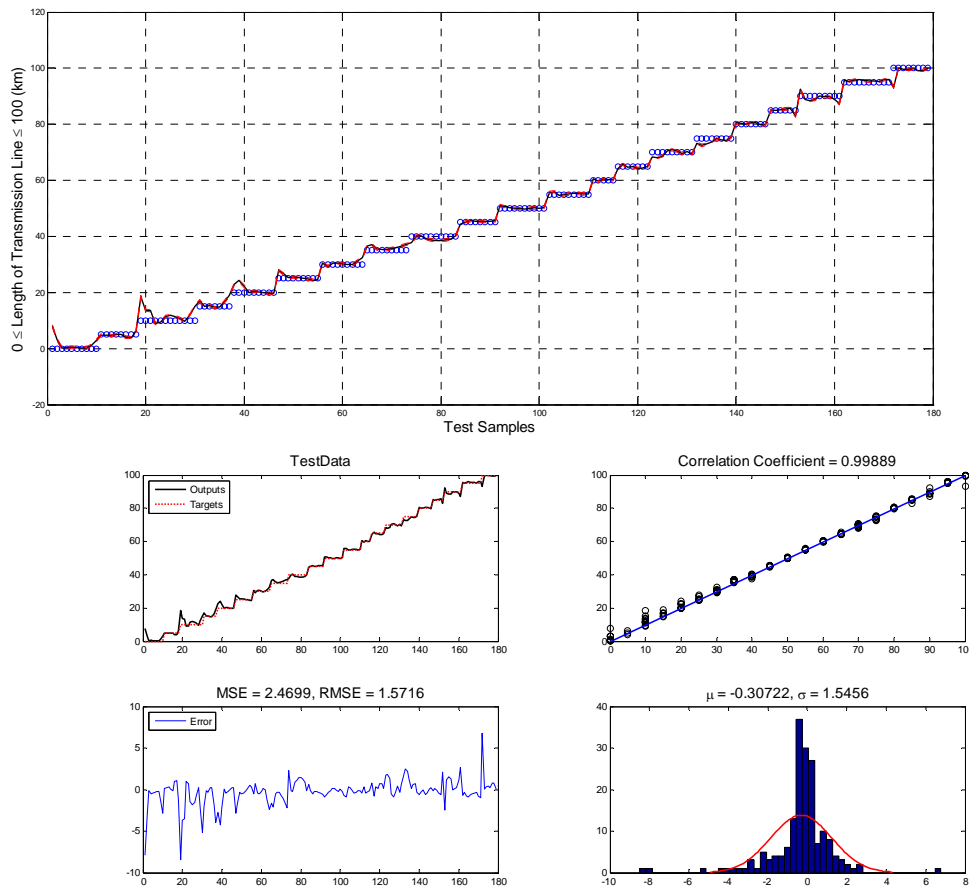| Fault type	Test fault real location (km)	WT-SVR		WT-MLP	
		Test fault estimation location (km)	Error %	Test fault estimation location (km)	Error %
LG	84	83.7931	0.2069%	84.2641	0.2641%
LL	41	40.9888	0.0112%	43.5616	2.2516%
LLG	66	65.8507	0.1493%	65.0075	0.9925%
LLL/LL LG	11	11.4700	0.4700%	11.9031	0.9031%

Figure 11. Estimating fault location phase S to ground with respect to the test samples.

The location results show the sufficient accuracy for the locator algorithm (SVR).

6. Conclusion

A new short-circuit fault classification and location method on power transmission lines has been introduced in this paper. Discrete wavelet transform has been used as the original factor in feature extraction from three-phase voltage signals after fault occurrence and in the following, by applying some changes in the high-frequency detail components, they have been benefitted as input to the proposed algorithms.

The important features of the proposed method are: 1) for each phase, only a single db4 high-pass mother wavelet filter is used. 2) For fault classification and location, complex energy computations are not needed; only squaring and summing operation of the samples are required.

In fault classification, discrete wavelet transform (DWT) at a level (Level-1)has been utilized for data extraction in a quarter of cycle of the phases R, S, T and zero sequence of the post-fault voltage signals registered in measurement units. The faulted phases have been determined using support vector machine classifier with one radial basis function Gaussian kernel. The average classification accuracy of the proposed WT-SVM method for fault classification is 99.62%. The WT-SVM based approach shows better Efficiency for fault classification in transmission line.

In fault location, the features used in the support vector machines classifier have been normalized for the second time & they along with fault locations have been used as input to support vectors regression locator. It is interesting to note that the maximum fault location error with the combined wavelet-SVR is less than 0.3%. Also, the maximum fault location error with WT- SVR is less than WT-MLP for variation in fault resistance.

The performance of the proposed method has been tested through various scenarios in two-machine power system with one overhead transmission line. The software PSCAD/EMTDC has been utilized for fault scenarios simulation & the proposed method has been tested by using wavelet transform toolbox, support vector machines & support vector regression algorithm in the software MATLAB. As a result, it has been demonstrated that the proposed short-circuit fault classification and location (FCL) operations are rapid, very reliable and safe.

Appendix

Table 5. The study power system parameters

Transmission line positive & negative sequence impedance (ohm/km)	$3.26 + j36.743[\Omega/km]$
Transmission line zero sequence impedance (ohm/km)	$32.15 + j111.753[\Omega/km]$
Source positive sequence impedance(ohm)	$15.057\angle85° = 1.31 + j15[\Omega]$
Source zero sequence impedance (ohm)	$26.702\angle85° = 2.33 + j26.6[\Omega]$
Apparent power(MVA)	$685[MVA]$
Rated voltage (KV)	$400[kV]$
Source 1 phase angle(degree)	$30[deg]$
Source 2 phase angle(degree)	$0[deg]$
Frequency (hertz)	$60[Hz]$
Transmission line length (km)	$100[km]$

7. References

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