

Accurate Fault Classification and Section Identification Scheme in TCSC Compensated Transmission Line using SVM

Pushkar Tripathi, Abhishek Sharma, G. N. Pillai, and Indra Gupta

Abstract—This paper presents a new approach for the protection of Thyristor-Controlled Series Compensator (TCSC) line using Support Vector Machine (SVM). One SVM is trained for fault classification and another for section identification. This method uses three phase current measurement that results in better speed and accuracy than other SVM based methods which used single phase current measurement. This makes it suitable for real-time protection. The method was tested on 10,000 data instances with a very wide variation in system conditions such as compensation level, source impedance, location of fault, fault inception angle, load angle at source bus and fault resistance. The proposed method requires only local current measurement.

Keywords—Fault Classification, Section Identification, Feature Selection, Support Vector Machine (SVM), Thyristor-Controlled Series Compensator (TCSC)

I. INTRODUCTION

DUE to advantages offered by series compensated transmission lines, their presence is consistently increasing in modern power system [1]. The conventional protection schemes are found to be inadequate either due to the operation of gap or varistor protection. The situation is worsened with applications of controllable series compensation using TCSC. Thus it is suggested that new protection approach should be investigated [2].

Detection, classification and location of fault are three main parts of transmission line protection. Detection requires identification of the occurrence of fault as soon as possible. Classification of faults consists of identification of the type of fault. This information is required for fault location and repair analysis. Fault Classification also leads to faulted phase selection this improves system stability with the help of single pole tripping [3]. Section identification further helps in zone identification and location of fault to speed up the repairing process. Fault classification and section identification is a difficult task for series-compensated transmission lines. Different methods [4] -[16] have been proposed for this purpose. Christopoulos and others [4] proposed an algorithm based on traveling waves, an algorithm using adaptive Kalman filtering technique was proposed in [5].

Various fault classification and section identification techniques have been proposed by different researchers for series compensated transmission lines using different types of neural networks such as Error Back Propagation Neural Network (EBPNN), Radial Basis Function Neural Network (RBFNN) and Fuzzy Neural Network (FNN) [6]-[8]. Few algorithms using Fuzzy logic, Wavelet transforms and higher order statistics have been proposed by different researchers [9]-[11]. Shortcomings of aforementioned methods are discussed in [12]-[14].

SVM based method with wavelet transform has been proposed in [12]-[15] but these methods increase overhead of pre-processing that too with high sampling rate for longer duration. Support Vector Machine (SVM) based fault classification scheme is proposed in [13] and encouraging results have been reported. However, in their method current samples and firing angle are given as input to SVM but these inputs are collected from two different location situated 150 km away from each other, this puts overhead of communication on their method. Recently in [14], an SVM based scheme is proposed without firing angle as input. It feeds post-fault current samples of one cycle period at the sampling rate of 4 kHz but used with fixed compensation. Moreover, in [14] authors have reported results by tuning the parameters of SVM on testing set (without standard practice of validation or cross-validation) which may cause overfitting, in turn this may lead to inflated accuracy [16]-[17].

In this work, we have achieved improved results even with variable compensation (TCSC), in lesser time and with lesser sampling rate (1 kHz). The proposed method is highly accurate (almost 100%) and it removes some physical constraints related to real-time data acquisition. At the same time, it also reduces the decision time by a large extent. The improved performance is a result of more informative input features to classifier and unique architecture of SVM (single multiclass SVM). 10 half-cycle-post-fault-current samples at the sampling frequency of 1.0 kHz from every phase (total 30 samples) were fed as inputs to the SVM from only one location i.e. the relaying end, providing a better practical solution with improved accuracy.

System considered for simulation is described in section II. A brief introduction of SVM is given in section III, and then

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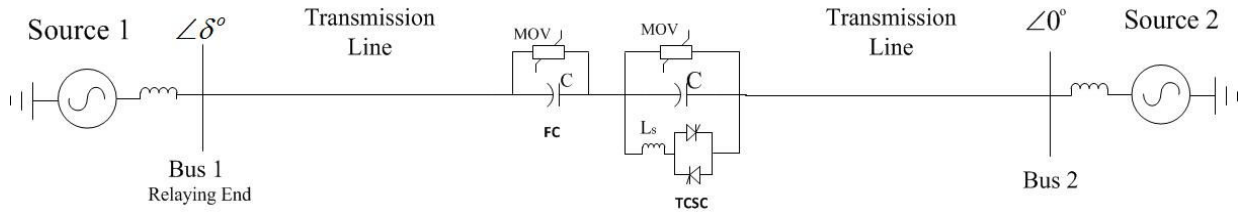


Fig. 1 Single Line diagram of system used

steps taken in training and testing of SVM are described at length in section IV. Section V presents Classification and identification scheme, comparative study with previous methods is done in section VI and finally conclusion is given in section VII.

II. POWER SYSTEM MODEL

A 400 kV, 50 Hz power system is used for simulation studies, which has two sources (representing two areas), and 300 km long transmission line having TCSC at the center of it as shown in Fig. 1. Compensation of line varies from 30% (at firing angle 180°) to 40% (at firing angle 150°). Bus 1 is taken as relaying end and all the data is collected only from relaying end. This model is developed using standard library components available in PSCAD/EMTDC [18]. The transmission line has been represented using the Bergeron line model. The source and line parameters are given in the Appendix-A. A typical protection scheme of a TCSC consists of a Metal Oxide Varistor (MOV), an air gap, discharge reactor and a bypass switch. In the case of fault voltage across the TCSC is limited by MOV. When energy of MOV reaches near to its allowable limit the gap is fired to protect both TCSC and MOV. After a few cycles the capacitor is reinserted by manual control [2]. Voltage rating of MOV is decided on the basis of maximum instantaneous voltage across MOV under normal conditions. This maximum voltage occurs when compensation level is maximum (4%) and both source impedances are minimum (75%).

III. SUPPORT VECTOR MACHINE

A. SVM

A classification task usually involves training and testing of some data instances. Each instance in the training set contains one "target value" (class labels) and several "attributes" (features). The goal of SVM is to produce a model that predicts the target value of unseen data instances. This property is popularly termed as generalization.

The discriminant function of SVM classifier is defined as $f(\mathbf{x}) = \mathbf{w} \cdot \boldsymbol{\phi}(\mathbf{x}) + b$ where \mathbf{w} is weight vector, b is bias $\boldsymbol{\phi}(\mathbf{x})$ is a mapping function to map the input pattern \mathbf{x} into higher dimensional space H . Using principle of structural risk minimization following minimization problem is formulated with cost function:

$$J(\mathbf{w}, \xi) = \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_i \xi_i \quad (1)$$

subjected to

$$y_i (\mathbf{w} \cdot \boldsymbol{\phi}(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad (2)$$

$$\xi_i \geq 0, \text{ for } i = 1, 3, \dots, l$$

where C is regularization parameter and ξ_i are measure of error in case of nonseparable data points and y_i is the class label of i^{th} data point. The solution which minimizes the above cost function, subject to the constraints in Eq. (2) can be obtained using the following dual formulation.

maximize:

$$L_D = \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \quad (3)$$

subjected to:

$$0 \leq \alpha_i \leq C \quad (4)$$

$$\sum_i \alpha_i y_i = 0 \quad (5)$$

where, α_i 's are lagrangian multipliers, $K(\mathbf{x}, \mathbf{y})$ is known as kernel, it is a non-linear function and defined as

$$K(\mathbf{x}, \mathbf{y}) = \boldsymbol{\phi}(\mathbf{x}) \cdot \boldsymbol{\phi}(\mathbf{y}) \quad (6)$$

The solution is then given by

$$w_o = \sum_i^{N_S} \alpha_i y_i \boldsymbol{\phi}(\mathbf{x}_i) \quad (7)$$

where, N_S is the number of support vectors.

If $f(\mathbf{x})|_{\mathbf{w}=w_o} < 0$ class-I

If $f(\mathbf{x})|_{\mathbf{w}=w_o} > 0$ class-II.

Interested readers can further consult [16], [17], [19], [20].

B. SVM Kernel Functions

The kernel function in an SVM plays the crucial role of mapping the input vector into a high-dimensional kernel space. In the present study, radial basis function (RBFs) kernel has been used since by experiments authors have found that in this application RBF performs better than other popular valid kernels i.e. Linear, Polynomial. It is defined as follows:

$$K(\mathbf{x}, \mathbf{y}) = \exp(-\gamma \|\mathbf{x} - \mathbf{y}\|^2) \text{ where, } \gamma = \frac{1}{2\sigma^2} \quad (8)$$

where, σ is width of Gaussian function.

C. Multi-class SVM

SVM is essentially a binary classifier so different strategies are required to convert it into multi-class classifier. "One against one" and "one against all" strategies are widely used multi-class SVM methods. "One against one" is the most popular method, moreover numerical experiments in [21] have shown that 'one-against-one' method is more suitable for application similar to our problem (i.e. when both number of classes and number of attributes are small). So this method is used here for fault classification and section identification.

D. Parameter Selection and Training

Once the training instances are obtained from simulation, the next step is to determine the optimal parametric setting of the any classifier (here SVM). For avoiding overfitting and giving correct measure of generalization capability of classifier, there are two standard procedures for selection of optimal parameters one is Validation and other is Cross-Validation (CV) [16], [17]. In present work, SVM parameter associated with RBF kernel (γ) is adjusted along with regularization parameter C, by using 5-fold CV. Then using these parameters SVM is trained for complete training set and tested on separate testing set.

IV. SVM'S TRAINING AND TESTING

A. Data Generation

The fault simulation studies have been carried out on PSCAD [18]. Variations in parameter values chosen in these studies are shown in Table I.

TABLE I
CHOSEN VALUES OF PARAMETERS FOR SIMULATION STUDY.

S. No.	Variation For	Range	No. of Runs
1	Fault Type	All 11 types of faults	11
2	Firing angle	150° to 180°	1
3	Fault resistance	5 Ω to 200 Ω	1
4	Fault inception angle	0° to 360°	5
5	Load angle at bus 1	10° to 30°	2
6	Source impedance	75%, 100%, 125% (both sources)	3 \times 3 = 9
7	Fault Locations	0 to 150 km (both sides of TCSC)	8 \times 2 = 16
	Total Runs	11 \times 1 \times 1 \times 5 \times 2 \times 9 \times 16 = 15840	

Except source impedance, value of all the parameters were selected randomly (uniform random distribution) between their given range. Parameters 1 to 5 were changed using multiple-run component of PSCAD [18] while 6 and 7 are varied manually. Thus, total 15,840 combinations of above mentioned parameters have been simulated. Out of these 15,840 data points, 10,000 are taken for testing and remaining 5,840, for training. Taking such a large variation in training-data points endows this SVM model with good prediction capability under real-life conditions. At the same time, taking large numbers of testing points ensures that the reported results are correct measure of generalization capability of classifier i.e. there is no overfitting or inflated accuracy. Extensive experiments are performed by taking different number of training instances at a time (500, 1000 ... 5500 and 5,840).

B. Feature Selection

Selection of good features is very important aspect of designing any classifier [16], [17]. For different objectives, different parameters of a system can be selected as the input signals to the classifier. Here 10 samples of currents from each

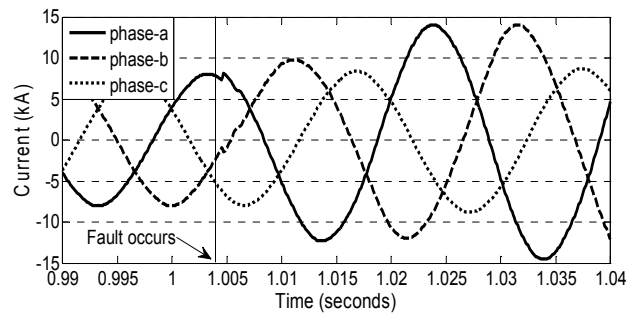


Fig. 2 Fault Current for ab-g fault

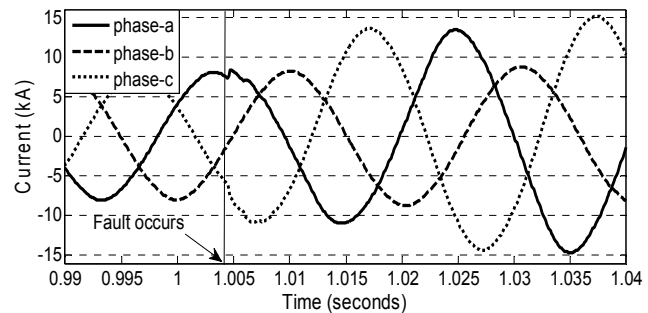


Fig. 3 Fault Current for ac-g fault

phase (total 30 samples, just after the inception of the fault) were selected at a sampling frequency of 1.0 kHz while power system frequency is 50-Hz i.e. 10 samples are taken from first half cycle duration of line current from each phase. The current instances were scaled properly (0 to 1) before feeding them to the classifier. It is obvious that increasing the number of samples of post fault period while keeping the sampling frequency fixed will give better accuracy but one cannot have the luxury of longer post fault duration since longer the fault period the larger will be its ill effects on the system. Consequently, there exists a trade-off between sampling length and accuracy. Hence it is decided to take 10 post fault current samples after experimentation.

The feature set should contain most relevant information for better classification. In [14], current samples from different phases are fed into corresponding phase classifiers and in [13], samples only from single phase were taken as inputs. So, the input features do not allow the comparison between different phase currents which is very important discriminating feature for faults. The rationale behind this could be understood from Fig. 2 and 3. The figures show the three phase currents for ab-g and ac-g fault respectively. It can be easily deduced that the current in phase 'a' is nearly the same in both faults. So, the current of phase 'a' only fails to discriminate between the two faults namely, ab-g and ac-g. The same holds for faults 'ab-g' and 'bc-g' when current samples of phase 'b' only are fed and so on. However, it is easy to distinguish between the two faults by observing all the three phase currents simultaneously. So, feeding current samples from all the three phases provides valuable discriminative information which leads to significant improvement in performance. So in proposed method, the current samples from all the three phases were fed to a single multi-class classifier enabling it to capture the discriminating

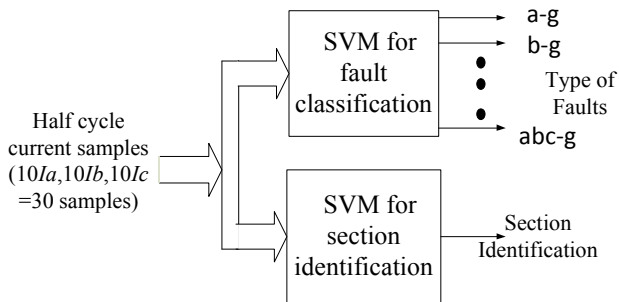


Fig. 4 Proposed protection scheme

information in a better way. This resulted in improved speed and classification accuracy up to 100%. Moreover, this intelligent choice of feature set leads to several modifications and improvements in existing methods which are discussed at length in Section-VI.

V. CLASSIFICATION AND IDENTIFICATION SCHEME

Since fault classification and section identification are two totally different tasks therefore they cannot be clubbed into one multiclass classifier. Hence the proposed method makes use of two SVM classifiers, one for classification of fault (multiclass SVM) and other for section identification (binary SVM classifier). The schematic diagram of proposed method is shown in Fig. 4. The fault classifier is a 10-class SVM which classifies the 10 types of fault namely, a-g, b-g, c-g, a-b, b-c, c-a, a-b-g, b-c-g, c-a-g, a-b-c/a-b-c-g. The second SVM identifies the section in which the fault has occurred by using the same feature set. So, it determines whether fault has occurred in section-1 (between relaying end and TCSC) or it has occurred in section-2 (between TCSC and other terminal of transmission line). The use of only two classifiers reduces the model complexity significantly. It is assumed that the directional sensing and fault detection units take care of directional discrimination and fault detection problems. Training and testing is performed on libsvm-mat-2.88-1toolbox [22].

VI. IMPROVEMENTS ACHIEVED

It should be noted that for all the performance graphs, testing is done on 10,000 testing instances while number of training instances is varied, to compare training efforts required for achieving required level of accuracy.

A. Better Ground Detection

In [12]-[14] phase and ground detection are dealt separately for classification of fault i.e. the involved phase (a, b or c) is detected using one classifier and ground is detected using a separate. Detection of ground involvement in the fault requires zero-sequence-current component in one way or the other, which requires the zero-sequence current to be determined, adding an extra process to be dealt with. Proposed method can achieve nearly perfect accuracy without making explicit use of zero-sequence-current component, eliminating the additional processing needed to acquire the zero-sequence-current.

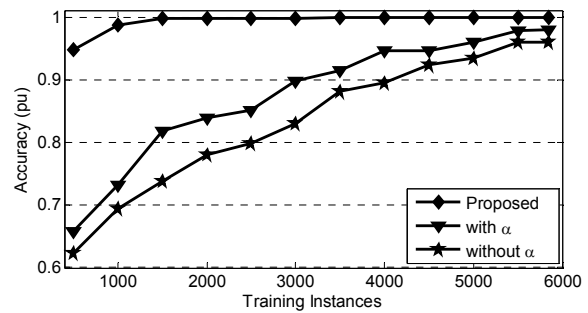


Fig. 5 Accuracy of fault classification Vs no. of training instances

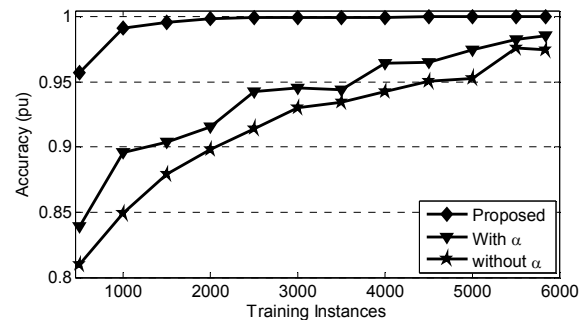


Fig. 6 Accuracy of section identification Vs no. of training instances

B. Better Accuracy with Lesser Complexity

The proposed method gives an accuracy of 100% (with 5000 and above training instances) which is not achieved so far to the best of our knowledge. Various researchers have reported an accuracy of around 97% for the same task [10]-[13]. However, some others have achieved accuracy above 99% [23] on simpler power system configuration (TCSC at one end) but by significantly increasing the complexity of the fault classification system. On the other hand, proposed method is fairly simple. The relative performance of the proposed method can be observed from Fig. 5. The figure provides a variation of performance of the methods with the number of training instances. The figure clearly shows that proposed method outperforms previous SVM based method [13] in both cases; when firing angle (α) is taken as input and when it is not. The former is termed as 'With α ' and later is termed as 'Without α '. It can be observed from the figure that proposed method outperforms other methods by a margin of more than 30% when only 500 instances are taken for training. Moreover, near 100% accuracy is obtained by the proposed method using only 1500 training instances while other methods are only 75% accurate. It signifies that the proposed method is significantly better than other methods even when small training data is available. Practically, the data available for training is not much so the proposed method is even more significant improvement in this aspect. For the purpose of comparison, Table II shows results of proposed method and Table I shows results of one other SVM based method [14] for fault classification accuracy for different fault types. Although less complex system (using fixed capacitor) was used, the accuracy is less than the

TABLE II
FAULT CLASSIFICATION ACCURACY FOR DIFFERENT FAULT TYPES BY PROPOSED METHOD (2500 TRAINING INSTANCES)

Fault type	No. of test cases	no. of mis-classification	no. of correct classification	Accuracy (%)
L-g	3347	2	3345	99.94
L-L-g	3109	7	3102	99.77
L-L-L/L-L-L-g	1009	0	1009	100
L-L-g	2535	0	2535	100
Total	10000	9	9991	99.91

TABLE-III
FAULT CLASSIFICATION ACCURACY FOR DIFFERENT FAULT TYPES REPORTED IN [15] (FOR 3600 TRAINING INSTANCES)

Fault type	No. of test cases	no. of mis-classification	no. of correct classification	Accuracy (%)
L-g	7560	193	7367	97.447
L-L-g	7560	105	7455	98.611
L-L-L/L-L-L-g	2520	0	2520	100
L-L-g	7560	29	7531	99.616
Total	25200	327	24873	98.703

proposed method. Moreover, in [14] the results are reported with overfitting (without validation of cross validation) while method proposed in present paper is tested as per as the standard procedure and still exhibited better performance.

Also the proposed method provides 99.85% accuracy in section identification (using 2000 training instances as shown in Table-IV) as compared to 91.53% provided by [14]. From Fig. 6 it can be seen that gap between the accuracy of proposed method and existing method reduces as number of training instances increases.

C. Better Speed

The speed of proposed method is much better than previous SVM based method [13]. Fig. 7 shows the variation in testing time with the number of training data examples. It should be noted that the time shown in the Fig. 7 is not the actual time but the normalized time to facilitate better comparison. It clearly shows that proposed method takes around one third time for same performance. As far as the application of fault classification is concerned, time taken for training is not much important because training is performed offline but time taken in prediction of fault (testing time) is important because testing is performed in real-time (however time taken in training by proposed method is lesser).

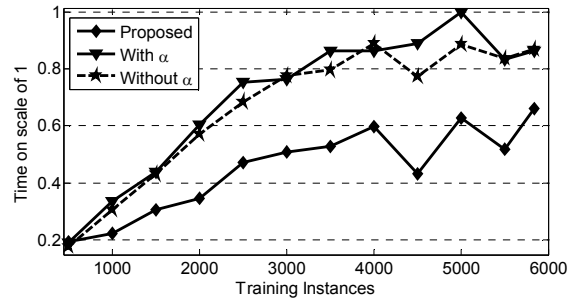


Fig. 7 Prediction time for fault classification

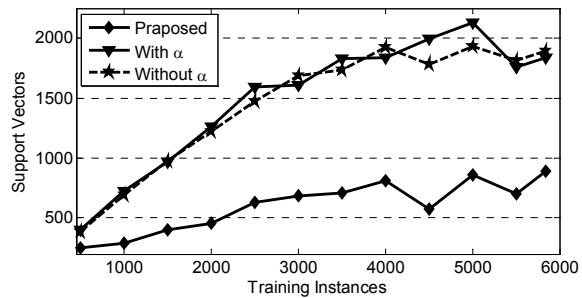


Fig. 8 No. of support vectors for fault classification

Prediction time not only depends on dimension of input vector but also on number of support vectors (number of evaluations of Kernel function), as number of support vectors (SV) increases time taken for predicting fault also increases. Fig. 8 shows the variation in number of SVs selected against the number of training instances. It clearly shows that the number of SVs is fairly lesser than the other methods. Because of this proposed method takes lesser time for prediction. Comparatively lower number of SVs also indicate that there is no overfitting in the proposed case.

Similarly proposed section identification scheme is faster owing to the lesser number of SVs. Table-IV gives summary of various results obtained by the proposed and existing SVM based method [13] for 2000 training instances to give glimpse of results in quantitative terms, as detailed results cannot be given due to space constraints. Since number of SVs are machine independent, but time given in Table-IV may vary on different machines, therefore training and testing time are given only for relative comparison. Specification of machine used is given in Appendix-B.

TABLE-IV
SUMMARY OF VARIOUS RESULTS OBTAINED BY THE PROPOSED AND EXISTING SVM BASED METHOD (FOR 2000 TRAINING SAMPLES)

Description of feature (input) vector	Description of label vector	C	γ	Accuracy %	Time (seconds) taken for training	Prediction time for 1 instance (ms)	no. of SVs
101a, 101b, 101c i.e.30 current samples (proposed)	10 types of fault	32	8	99.84	0.144813717	0.9912739	458
101a, 101b, 101c i.e.30 current samples (proposed)	Section Identification	256	8	99.85	0.134575146	0.3025302	157
10 1a i.e. current samples from phase a + firing angle (α)	faulty phase	32	4	83.96	0.228417605	1.7325835	1263
10 1a i.e. current samples from phase a + firing angle (α)	section identification	256	16	91.53	0.374174669	0.837786	709
10 1a i.e. current samples from phase a	faulty phase	512	8	78.06	0.621778222	1.6393754	1224
10 1a i.e. current samples from phase a	section identification	512	8	89.84	0.355411802	0.94505	824

D. Physical Feasibility

The method proposed by [13] takes the firing angle as a crucial input which requires a communication system from TCSC to relaying end. Moreover, removal of firing angle from their input decreases the accuracy (Fig. 5) and increased the testing time (Fig. 7). It shows the dependence of performance on firing angle in [13]. On the other hand, the proposed method does not require firing angle as an input and this relieves from the burden of communication system.

VII. CONCLUSION

A novel method for fault classification and section identification for series compensated lines having TCSC has been presented. This method uses more informative input feature vector for both purposes. As a result it achieved high accuracy under a wide variation in system conditions. Moreover, it significantly reduces the time required for successful operation. It requires local tree phase current measurement and does not require firing angle as input. Therefore it does not require communication infrastructure. It also does not require any preprocessing such as wavelet transform and zero-sequence-current component calculation etc.

APPENDIX

A. System Parameters:

(i) Source 1:

Positive sequence impedance = $15.06 \angle 85^\circ$ (100%)

Zero sequence impedance = $26.70 \angle 85^\circ$ (100%)

Phase angle = varied between 10° to 30°

Frequency = 50 Hz

Voltage at terminal = 400 kV.

(ii) Source 2:

Same as Source 1 only phase angle is kept constant (0°)

(iii) Transmission-Line Data:

Length = 300 km

Voltage = 400 kV

Positive-sequence impedance = $8.25 + j94.50 \Omega$

Zero-sequence impedance = $82.50 + j308.00 \Omega$

Positive-sequence capacitive reactance = $224.97 \text{ M}\Omega \cdot \text{m}$

Zero-sequence capacitive reactance = $374.67 \text{ M}\Omega \cdot \text{m}$

B. Specification of Machine Used:

Intel® Core™2 CPU, E7400@2.80 GHz, 4 GB RAM.

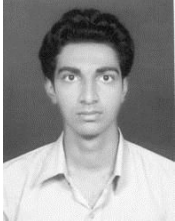
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