Fault detection and location based SVM for three phase transmission lines utilizing positive sequence fault Components

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Abstract: *The reliable and efficient operation of three-phase transmission lines is crucial for ensuring the stability and integrity of electrical power distribution networks. Fault detection and location represent critical aspects of maintaining grid reliability. This research paper introduces a novel approach for fault detection and location in three-phase transmission lines, specifically targeting positive sequence faults. The proposed method leverages Support Vector Machines (SVM) as a robust machine learning technique to analyze the electrical signals from the transmission lines. Positive sequence fault signals are extracted and processed to develop a fault detection and location model. Unlike traditional methods that rely on complex mathematical algorithms or time-consuming simulations, this approach offers a data-driven solution for fault detection and location. The research focuses on the identification of positive sequence faults, which are common and often indicative of early-stage problems in the power grid. By utilizing SVM, the model demonstrates high accuracy and efficiency in identifying these faults, minimizing false alarms, and enhancing the reliability of fault detection systems. Furthermore, the model's ability to pinpoint the location of the fault within the transmission line is a valuable asset for power grid operators. Rapid fault localization aids in reducing downtime, improving response times, and ultimately ensuring the continuous supply of electricity to consumers.*

Keywords: Fault identification, Fault classification, Support Vector Machine (SVM), Positive Sequence Analyzer, Transmission lines, Electrical fault detection.

1 Introduction

Long transmission lines cover a lot of ground and are frequently subject to various issues. Short circuits between the lines and with the ground commonly result from environmental restrictions like storms, snow, and other similar events, as well as other little but natural worries like animals, birds, and even developing flora troubles. They trigger slight to major transmission line breakdowns. According to data [1], line failures are the most common electrical system defect. Numerous methods that use line data from one or more terminals to pinpoint the location of faults fall under the categories of analytical methods, methods based on artificial intelligence (AI), methods using magnetic sensors, methods using travelling waves, and methods based on software [2], [3], [4], [5].

Any transmission line protection system should have two main objectives: to increase reliability through high-speed directional relaying and fault classification. One of the most important tasks for safeguarding electricity transmission lines is classifying the fault type, such as whether it is a single-phase-to-ground, double-phase-to-ground, phase-to-phase, or three-phase type. Once the type of fault has been determined, finding the defect is essential[6–8].

Numerous methodologies have been employed over the past 20 years to classify faults in power transmission lines. For double-circuit lines, a combined unsupervised/supervised neural network-based fault classification technique [9] has been introduced. A modified digital distance relaying mechanism has been proposed in [10] specifically for inter-circuit errors. Furthermore, a clever strategy [11] based on ANNs has been developed to perform a number of protective relaying tasks, including fault detection (both forward and reverse), classification, and zone/section estimate, providing primary protection for 95% of the line length. For the diagnosis of faults in the electric power system, SVM, another paradigm of artificial intelligence technique, has been used [12–23]. The main advantage of SVM is that it requires fewer training patterns and trains faster. Furthermore, transmission line distance relaying has been implemented using SVM and radial basis function neural network [13]. SVM has been used to locate power transmission line failures in [14]. Additionally, wavelet and SVMs have been used to classify fault zones in [17] and identify fault zones in transmission lines with series compensation in [15,16].

To describe the detection, classification of faulty phase, and location of fault in two-terminal transmission line, DWT and artificial neural network (ANN) have been utilized [24, 25]. However, the placement algorithms for [24, 25] differ for grounded and non-grounded fault, which complicates computation. In [26], a guided protection method for the location and detection of double-circuit transmission line faults utilizing DWT and ANN was put out. In order to tackle the difficult non-linear optimization problem using AI techniques, deep neural network (DNN) has been developed as an alternative to ANN [27].

This study's main contribution is a novel integrated protective relaying method with an improved support vector machine algorithm for locating long transmission line faults. The proposed approach is capable of correctly locating and classifying a wide range of symmetrical and asymmetrical faults as well as some peculiar cases involving High Impedance Faults (HIF) and evolving faults, current transformer (CT) saturation/capacitive voltage transformer (CVT) transient, close-in faults, swing condition, source strength variation, etc.

In this paper we developed a fault location estimation, which is computed using positive sequence admittance of both ends of the line to identify the internal/ external faults precisely. The fault location algorithm has also been developed using positive sequence parameters. This approach is valid for all types of faults as positive sequence phasors exist for all faults unlike negative and zero sequence components.

The remainder of the document is divided into five sections. The works that already use the algorithm are described in Section 2. Section 3 explains the suggested model. Section 4 displays the power system simulation model.

The results of the detection and localization systems are displayed in Section 5. The discussion and conclusions are included in Section 6. Last but not least, we offer the reference directory.

Transdisciplinary (TD) research on "Fault detection and location based SVM for three-phase transmission lines utilizing positive sequence fault" involves a holistic approach that integrates knowledge and methodologies from multiple disciplines to address the complex challenges associated with fault detection and location in power transmission systems. This research goes beyond the boundaries of traditional disciplinary silos and incorporates insights from various fields such as electrical engineering, machine learning, data analytics, and signal processing. Here's a breakdown of how TD research operates in this context:

1.1 Integration of Diverse Disciplines:

1.1.1 Electrical Engineering:

TD research in fault detection and location for transmission lines draws extensively from electrical engineering principles. It involves a deep understanding of power systems, transmission line behavior, and fault characteristics.

1.1.2 Machine Learning and Data Analytics:

Machine learning techniques, particularly Support Vector Machines (SVM), are utilized for data analysis and pattern recognition. Researchers combine their knowledge of power systems with advanced data analytics to develop fault detection algorithms.

1.1.3 Signal Processing:

Signal processing techniques are applied to analyze voltage and current waveforms in the transmission lines. Researchers use their expertise in signal processing to extract meaningful information related to fault conditions.

1.2 Interdisciplinary Collaboration:

TD research encourages collaboration between experts in various disciplines. In this context, power engineers work closely with machine learning specialists, data scientists, and signal processing experts. This collaborative approach ensures that the research benefits from a wide range of perspectives and expertise.

1.3 Data Collection and Preprocessing:

Researchers collect real-world data from transmission lines, including voltage and current measurements during normal and fault conditions. This data is preprocessed to remove noise and prepare it for analysis.

1.4 Feature Extraction and Selection:

Signal processing experts identify relevant features in the data that can help distinguish normal operation from fault conditions. Machine learning experts assist in selecting the most appropriate features for SVM-based fault detection.

1.5 Development of SVM-Based Models:

Machine learning researchers design and train SVM models using the preprocessed data and selected features. These models are tailored to detect and classify positive sequence faults in transmission lines.

1.6 Cross-Disciplinary Validation:

Validation of the SVM-based fault detection models requires a multidisciplinary approach. Power engineers assess the models' performance based on their knowledge of transmission line behavior and fault characteristics. They provide critical insights and feedback to improve the models.

1.7 Practical Applications:

The ultimate goal of TD research in fault detection and location is to develop practical solutions that can be implemented in real-world power systems. Collaboration with industry professionals and policymakers ensures that the research has a meaningful impact on the reliability and efficiency of power transmission networks.

In summary, transdisciplinary research on fault detection and location in three-phase transmission lines utilizing positive sequence faults involves the integration of knowledge and expertise from diverse fields. This holistic approach fosters innovation and leads to more effective solutions for enhancing the reliability of power systems.

2 Methodology

Electricity is transported from generating stations to load centers via a network of transmission lines. Symmetrical faults (LLL and LLLG) and unsymmetrical faults (LG, LLG, and LL) may occur on the transmission line. These flaws have the potential to interrupt the supply while seriously harming the transmission and distribution system-connected equipment. Accurate detection and precise classification of fault events are essential for maintaining the stability, security, and dependability of the power system. The power system operator can decide whether or not to trigger asymmetrical circuit breaker tripping using this information.

This section provides a quick overview of the methods for fault detection and classification .Traditional line fault detection used to heavily rely on visual inspections of the faulted line parts resulting in long and tedious foot or aerial patrols. These methods were expensive and prone to more errors. Thus, the shift to automatic fault locators was not only desired, but also natural.

2.1 Fuzzy logic Technique

A fuzzy logic technique is used to locate the fault and to identify line to ground and line to line faults on a transmission line. Fuzzy technique consists of three steps ,as shown in Fig. 1.

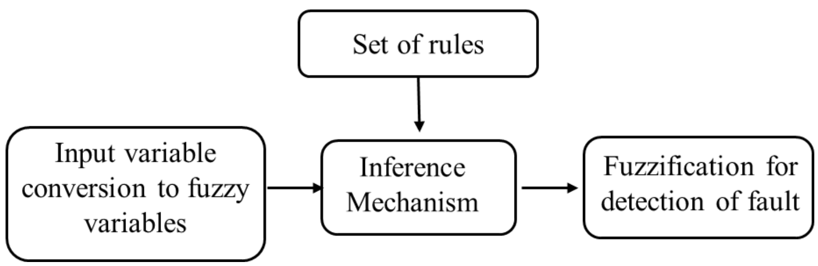

Figure 1: Structure of Fuzzy module

In the first step, input variables are first converted in to fuzzy variables. The next step then evaluates the overall truth grade using membership function. The final fuzzification step provides crisp outputs for fault location. Membership functions of input/output variables are based on designers' knowledge and experience. It applies a set of rules appropriate to the situation, which may overlap and even contradict each other. The final course of action is appropriate combination of all relevant situations. Although the choice of number, range and shape of membership function for a variable is ultimately based on subjective design choices and evaluation of the resulting system performance, the following points have been kept in mind to match the best possible results:

- Symmetrically distribute the fuzzy sets across the defined universe of discourse.
- An odd number of fuzzy sets for each variable is used. This ensures that Some fuzzy Sets will be in the middle.
- Overlap adjacent fuzzy sets to ensure that no crisp value fails to correspond to any set.
- Triangular membership function is used as this require less computation time than others.

Fig.2 indicates the T-function description

Triangular membership function is defined as

$$T(u; a, b, c) = \begin{cases} 0 & \text{for } u < a \\ \dfrac{u - a}{b - a} & \text{for } a \leq u \leq b \\ \frac{c-u}{c-b} & \text{for } b \leq u \leq c \\ 0 & \text{for } u > c \end{cases} \tag{1}$$

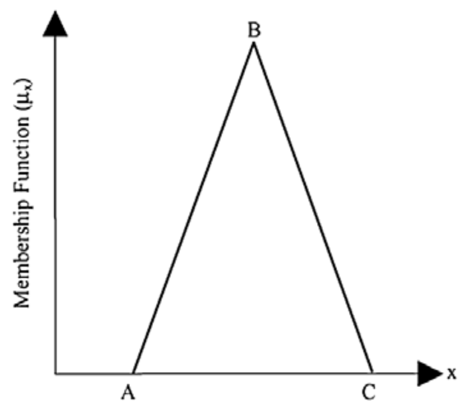

Figure 2: The T - function

2.2 Support Vector Machine (SVM) classification and prediction

SVMs are supervised learning techniques with corresponding learning algorithms to simplify fault data analysis, identify fault patterns, and be utilized for regression and classification analysis. By employing the kernel approach and implicitly transforming their inputs into high-dimensional feature spaces, SVMs achieve classification. In this work, multiclass SVMs are utilized to estimate the direction of defect, which is possible. The identification and estimation of the fault section fall under multiple classes. But because it determines whether a specific phase is faulty or not, fault phase identification is a two-class problem (fault or no fault).

SVM is used in fault diagnosis in two stages: training with known goals and testing with unidentified samples. The SVM modules receive data as input. The network is then trained with SVM using corresponding targets for the input training data. Re-substitution error (also known as mean square error) is then used to determine how well the training SVM networks performed.

SVMs can effectively do non-linear classification in addition to linear classification by implicitly mapping their inputs into higher dimensional feature spaces. This technique is known as the kernel trick. Input vectors are non-linearly transferred to a very high dimensional feature space by the machine, which conceptually embodies this approach. A linear decision surface is built in this feature space. High generalization ability of the learning machine is ensured by unique qualities of the decision surface.

The trained SVM network created for various jobs is then tested against a variety of fault instances to produce outputs. Below fig 3 shows the SVM classification characteristics.

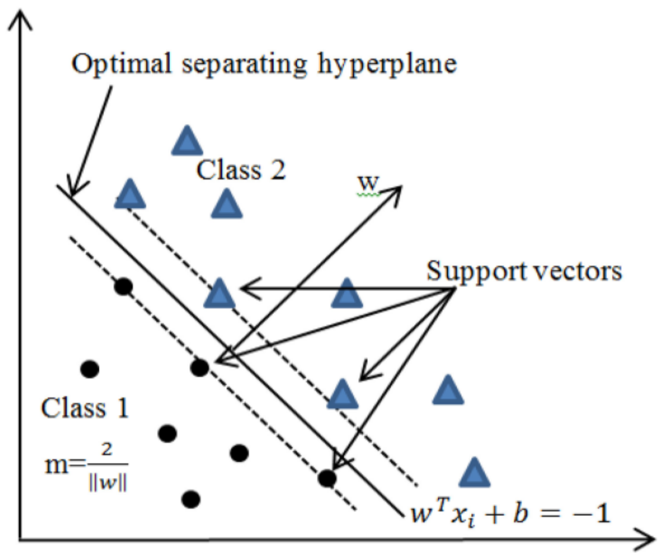

Figure 3: SVM classification

The SVM model uses the 3-phase currents, voltages, and time and frequency parameters as input features. Let's have a look at a two-class training data set with N data points, $\{x_i, y_i\}_{i=1}^{N}$. The ith real-valued input vector is designated by the notation x_i, and its associated class, y_i, has a value of either +1 or -1. The equation yields a hyperplane that divides these points into their respective classes.

$$w^T x_i + b = 0 \tag{2}$$

as shown in Fig. 1. '***w***' and '***b***' represent weight vector and bias term (vector), respectively, and determine the position of the separating hyper-plane. Finding the value of w and b that maximizes the separation between the classes is the goal of training. The separation margin (m) can be demonstrated to be provided by

$$m = \frac{2}{||\boldsymbol{w}||} \tag{3}$$

With training, the maximum value of "m" should be raised for better separation, while the minimum value of "w" should be reached. Consequently, the SVM can be created by maximizing v(w) for linearly separable data.

$$v(w) = \frac{1}{2} w^T w \tag{4}$$

Subject to

$$y_i(w^T x_i + b) \geq 1 \tag{5}$$

Providing construction of multi-class SVMs, where we build a two-class classifier over a feature vector $\emptyset(x, y)$derived from the pair consisting of the input features and the class of the datum. At test time, the classifier chooses the class $y = \arg\max_{y'} w^T \emptyset(x, y')$. The margin during training is the gap between this value for the correct class and for the nearest other class, and so the quadratic program formulation will require that

$$\forall i \forall y \neq \boldsymbol{y}_i w^T \emptyset \boldsymbol{x}_i, \boldsymbol{y}_i - w^T \emptyset\, (x_i, y_i) \geq 1 \tag{6}$$

A multi-class formulation of different types of linear classifiers can be provided using this general method. It is also a straightforward example of a generalization of classification where the classes may be arbitrary structured objects with relationships defined between them rather than just a collection of independent, categorical labels. Below is a line diagram of the system that has been put into use. Thus, the prediction of fault is done using SVM as discussed above.

Proposed simulation model single line diagram is shown in below fig 4.

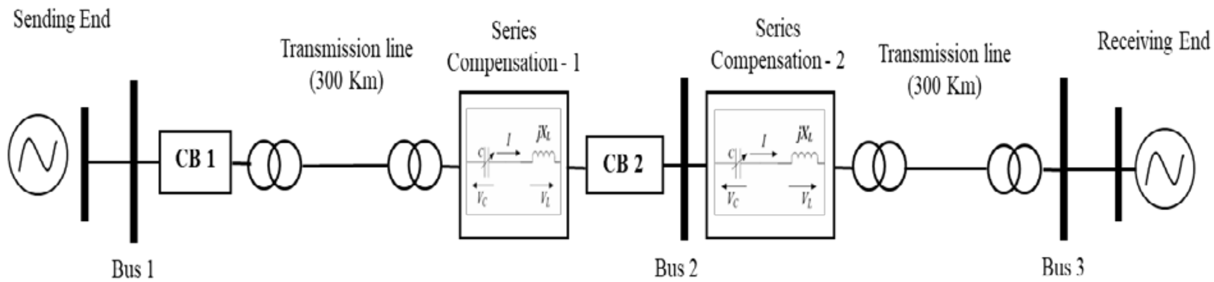

Figure 4: Line diagram of system

3. Methods:

In this implementation, we have indicated that we are utilizing Positive Sequence Analyzer. The ppropòsed work flow for calculating the features is indicated in below fig-5 .We consider following six parameters for input of SVM.

1. Bus1 Voltage (V1)
2. Bus1 Current (I1)
3. Bus 2 Voltage (V2)
4. Bus 2 Current (I2)
5. Positive Sequence Voltage
6. Positive sequence Current

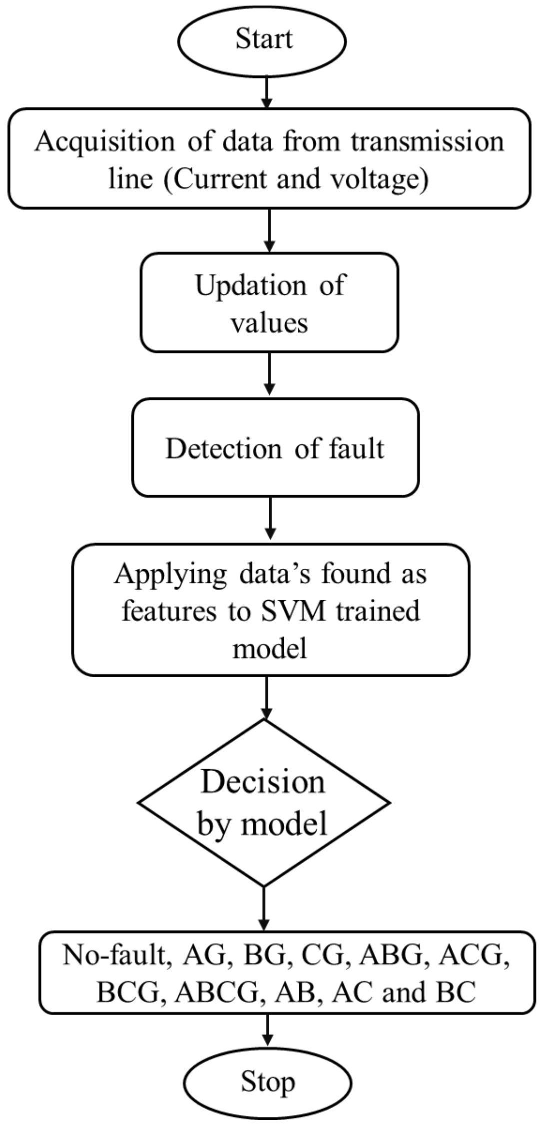

Figure 5: Proposed work flow for calculating the features

Only positive sequence current flows for symmetrical faults (LLLG or LLL), and even for LLLG, the amplitude of negative and zero sequence would be close to zero, therefore we can argue that only positive sequence represents a symmetrical fault.

No zero (very little) sequence flows in an asymmetrical fault mean that, for line to line (LL), positive equals negative if not grounded. Therefore, the fault would be line to ground (LG) or line to line and ground (LLG) if the zero-sequence component is significant. The error would be LLG if positive were equal to positive plus zero, LG if positive, negative, and zero sequences were all identical. Even when the load is out of balance, there is still a sizable negative sequence that can be utilized to identify the imbalance. As a result, the input is used at the beginning in positive sequence.

With this methodology, various faults are used each time to evaluate the classification performance. For every defect type, this process is repeated. This validation method is used in this study to inspect, confirm, and validate the SVM model's classification abilities. As a result, a generated SVM model may be installed in the substations' protective relays. The classification accuracy of the proposed SVM-based scheme is verified with the testing data set, and its performance is evaluated

3.1 Simulation model

In this study, a 300 km double-fed, 400 kV transmission line has been taken into consideration. Fig. 6 depicts the simulated power system and relaying model. The system was created using Simulink and MATLAB. The analyzed outcomes are displayed below.

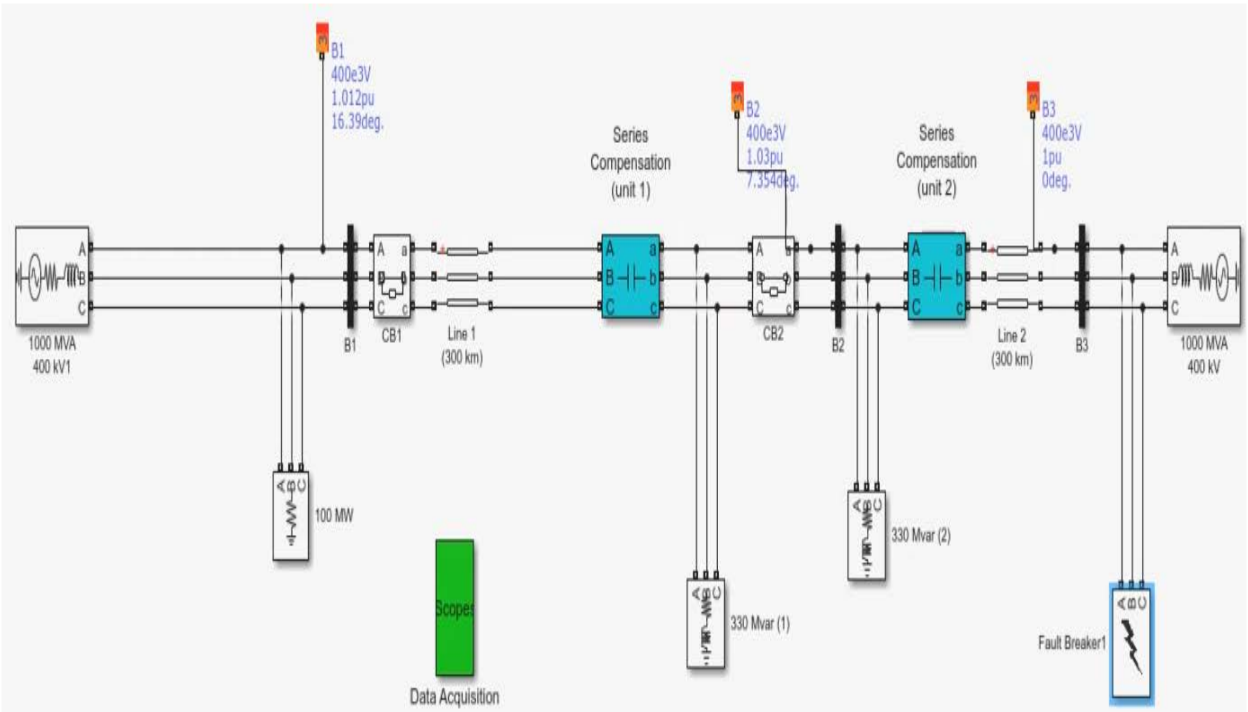

Figure 6: Simulation model for 400 KV 300 km double fed transmission line with SVM

3.2. Detection of external Fault:-

The prediction of external fault is illustrated in Fig 7

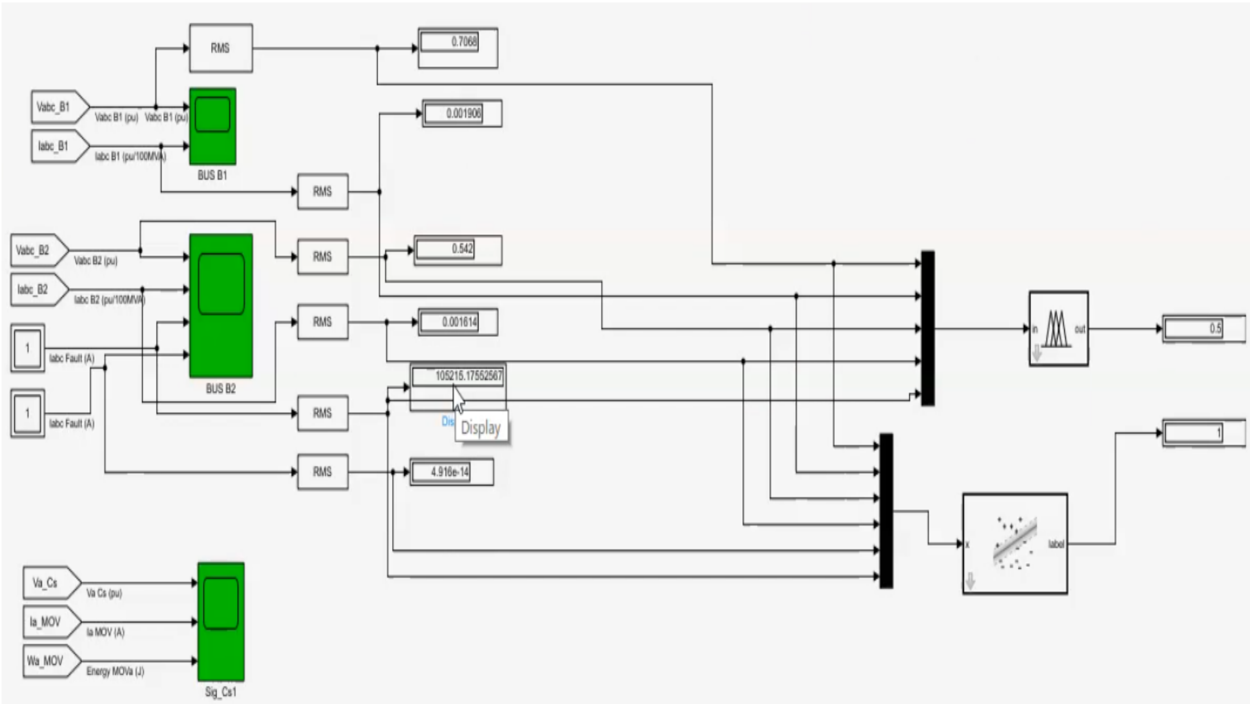

Figure 7: Simulation output of transmission line during external fault.

Table 1 Types of External fault Considered

Type of Fault	Fault Resistance	X/R RATIO Variation	Source Power Variation	Load Variation	Line Length Variation
AB AC BC ABG ACG BCG ABC ABCG AG BG CG	1)0.001 2)10 3) 20 4) 30 5)40 6)50 7)60	x/r ratio change to 20	SOURCE POWER change to 1500 MVA	LOAD VARIATION to 150 MW	Line 1 Length change to 100 km Line 2 Length change to 50KM Changing both Line1&Line2 length at same time

Therefore, the proposed scheme can realize fault detection of the whole transmission line, which is the core deficiency of the traveling wave-based scheme. The above-mentioned tables 1 and 2 shows that proposed scheme is successfully detecting and classifies different symmetrical and unsymmetrical faults along with some peculiar cases related to

- High Impedance Faults (HIF) and evolving faults is detected by varying the impedance as mentioned in column 2,
- Current transformer (CT) saturation/ capacitive voltage transformer (CVT) transients are also detected by varying corresponding values as mentioned in column 4 and 5,
- Directional relays use voltage as the polarizing quantity. When three-phase faults occur close to the relay bus, the available voltage becomes nearly zero and this creates a problem in estimation of the fault direction which is called as close-in fault (or near end fault). This is detected by placing the fault breaker close to bus.
- Swing condition and source strength variation based fault detection is also verified and detected.
- Distance variation of lines 1 and 2 are also done and verified for the fault detection as mentioned.

3.3. Detection of Internal Fault:-

As is obviously shown, the proposed fault detection scheme can accurately distinguish different fault types. For the internal short-circuit fault, the proposed SVM-based detection scheme can identify the fault inception swiftly for any position along the protected line. During the internal fault, the fault breaker is located internal of long transmission line is shown in Fig. 8

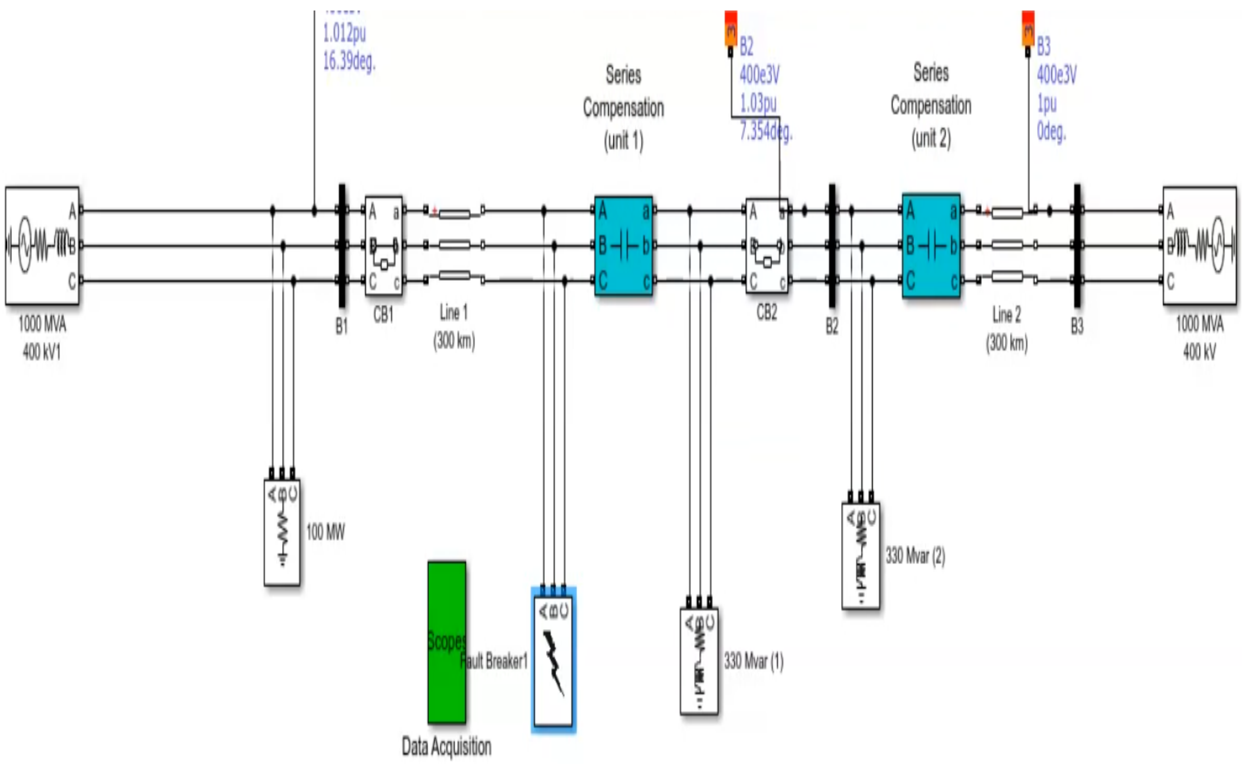

Figure 8: Simulation model for 400 KV 300 km double fed transmission line with SVM having fault internally

Table 2: Types of internal faults Considered

Type of Fault	Fault Resistance	X/R RATIO Variation	Source Power Variation	Load Variation	Line Length Variation
AB AC BC ABG ACG BCG ABC ABCG AG BG CG	1)0.001 2)10 3) 20 4) 30 5)40 6)50 7)60	x/r ratio change to 20	SOURCE POWER change to 1500 MVA	LOAD VARIATION to 150 MW	Line 1 Length change to 100 km Line 2 Length change to 50KM Changing both Line1&Line2 length at same time

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4. Results and Discussion

The testing data set was meticulously developed to encompass a range of fault scenarios, ensuring comprehensive evaluation of the line impedance based Detector and Classifier. The outcomes of these tests have been summarized in Table 3. In a healthy condition, where no fault is present, the expected output of both the fault detector and classifier should be zero. Conversely, in the presence of a fault, the anticipated output in the respective faulty phases should be one. Upon analyzing the data presented in Table 3, it becomes evident that following the occurrence of a fault, the output of the corresponding phases significantly increases, validating the effectiveness of the fault detection and classification system.

Table 3 Sample test results

Fault type	Fault location (Distance from the relay in km)	Fault resistance (in ohms)	Output of the SVM classifier			
			Phase A	Phase B	Phase C	Ground G
No fault	-	-	0	0	0	0
AG	100	10	1	0	0	1
AB	80	20	1	1	0	0
AC	50	30	1	0	1	0
BC	70	40	0	1	1	0
BG	90	50	0	1	0	1
CG	150	60	0	0	1	1
ABG	200	0.001	1	1	0	1
ACG	270	20	1	0	1	1
BCG	300	60	0	1	1	1
ABC	180	50	1	1	1	0
ABCG	210	40	1	1	1	1

The impedance variation is done to evaluate High impedance faults (HIF) in transmission line. Methods for detecting and classifying faults, it compares the most commonly known line parameters with the impedance measured in the event of a fault. Source strength are also varied and results are determined. According to test results, the approach's speed and selectivity are quite reliable and offer sufficient performance for a three-phase transmission line.

Accuracy: It is defined as the number of faults in the given input dataset that have been effectively categorised.

$$\text{Accuracy} = (TP + TN)/ (TP + TN + FP + FN) \qquad (7)$$

True positive (TP- the quantity of faults appropriately correctly classified as considered necessary), false positive (FP- the quantity of faults inaccurately foreseen as considered necessary), true negative (TN- the number of faults properly classified as not needed), and false negative (FN- the quantity of faults inaccurately indicated as not desirable) are the terms used in the measuring performance

Assuming the accuracy values are stored in the variables “accuracy, ACaccuracy, BCaccuracy, CCaccuracy, DCaccuracy”. A cell array is created with the names of our models as 'Model', 'Model2', 'Model3', 'Model4', 'Model5'. Then an array is created with our accuracy values as “[accuracy, ACaccuracy, BCaccuracy, CCaccuracy, DCaccuracy]”. Then accuracy table is obtained as given in Table 4

Table 4. Estimated accuracy table

Model Name	Accuracy
‘Model’	97.6220
‘Model2’	95.3692
‘Model3’	95.7447
‘Model4’	98.4981
‘Model5’	94.3680

All models have high accuracy, ranging from 95.37% to 98.37% which on overall have average accuracy of 95.8 %. This indicates that all models are performing well on the given dataset. Model 4 has the highest accuracy of 98.37%, while Model 2 has the lowest accuracy of 95.37%.

Mean while, simulation results verify that the proposed scheme can identify short circuit faults grounded with large resistance, grounding resistance and this can be verified by varying the parameters. This improves the detection failure that may occur on current changing based fault detection schemes with a short-circuit fault through high resistance grounding. Thus, the proposed method yields 95.8 % of accuracy in approximation.

4.1 Comparison of results with existing methods :-

Table5 shows the comparison of results with existing methods

Table5 comparison of results with existing methods

Parameters	**Reference [1]**	**Reference [2]**	**Reference [3]**	**Reference[4]**	**Proposed scheme**
Technique used	DWT, ANN	DWT, DNN	SCA, FIS	FDST, Travelling wave	SVM
Signal used	V, I	I	V	V,I	V,I
Fault resistance, Ω	15	140	40	300	0.01,10,20,30,40,50,60
Whether location algorithm dependent on fault type	Yes	No	Yes	No	No
Whether all types of faults can be located	Yes	Yes	Yes	Yes	Yes

5. Conclusions

In this work, a single ended mixed SVM based fault classification and defective phase identification technique is proposed. The approximation coefficients of the current signals, which are only measured at one end of the line. The suggested SVM-based technique has the advantage of being able to identify the fault in both primary and backup protection up to 95% of the line length. The suggested SVM-based relay only needs a small number of training patterns. The suggested method accurately locates 95.8% of all sorts of shunt faults in a variety of locations. According to test results, the approach's speed and selectivity provide adequate performance for a three-phase transmission line and are highly dependable. Although it is a one-time offline process, the training time needed to build an SVM network increases if training data size increases due to a change in system configuration. The proposed scheme is successfully detecting and classifies different symmetrical and unsymmetrical faults along with some peculiar cases related to High Impedance Faults (HIF) and evolving faults, current transformer (CT) saturation/ capacitive voltage transformer (CVT) transient, close-in faults, swing condition, source strength variation, etc. The comparative analysis with recent proposed techniques declared the potentiality and robustness of the scheme.

By embracing a transdisciplinary perspective, this research paper aims to contribute to the development of more reliable and efficient fault detection and location methods for three-phase transmission lines, ultimately enhancing the stability and resilience of modern power grids.

Authors' Contribution:

Ganesh Shingade contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing.
Dr Sweta Shah contributed to validation, analysis, investigation, visualization, supervision, and project administration.

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