Australasian Universities Power Engineering Conference, AUPEC 2020, Hobart, TAS, Australia, 29 November – 3 December 2020

Intelligent Fault Localization for Meshed HVDC Transmission Systems

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***Abstract*—Half-bridge Modular Multilevel Converters (HB-MMCs) enable the transmission of renewable energy from remote places to load centres with high levels of efficiency. Further, and relative to other MMC topologies, the HB-MMC is low in cost to implement. However, in cases where the severity of the fault increases beyond a given threshold, HB-MMCs could become blocked, which may lead to a grid collapse before the fault can be isolated. Therefore, an intelligent system is proposed to locate and isolate the exact fault path using Quadratic Support Vector Machine (QSVM) and Squared Exponential Gaussian Process Regression (seGPR) algorithms. This allows for timely fault clearance and, for meshed systems, identification of alternative power flow paths to achieve fault ride-through. Thus, the continuous operation of the grid under a fault condition can be assured. Converter simulation, data analysis and fault estimation are presented using MATLAB/Simulink to show the effectiveness of the proposed system.**

Keywords—MMC-HVDC, Half Bridge, Primary Protection, Backup Protection.

I. Introduction

Currently, there is a global drive to increase reliance on renewable energy sources. Such energy sources are often located distantly from loads, which gives rise to a need for long distance transmission line systems [1]. In this case high voltage direct current (HVDC) transmission is preferred to its AC counterpart, as losses are lowered [2], and attention has been placed on voltage source converter (VSC) based HVDC.

The VSC has key advantages such as flexible control, black-start capability, AC voltage control, network security and fast dynamic response [3]-[4]. The Modular Multilevel Converter (MMC) is the most commercially sought-after VSC type, having capacities and DC operating voltages up to 4000 MW and 800 kV respectively [5]-[6]. The appeal of MMCs derive from savings on cost and improvements in efficiency, as AC side filters and bulky transformers are not required [7]-[8]. If any of its modules fail, the MMC converter can still operate because of its redundant submodules (SMs). This protective feature of the MMC is called primary protection. However, in most severe fault cases, the MMC switching elements could be short-circuited to prevent further damage to the converter thereby affecting the continuous operation of the grid and Fault Ride Through (FRT) [9]. Achieving FRT, poses significant challenges to the implementation of MMC based HVDC grid systems because it is expected that the grid remains operative during a fault. [10].

As a result of the above limitation, several fault tolerant MMC SMs such as the Full-Bridge (FB), Clamp Double (CD), Alternate Arm (AA) types and all the hybrid designs were proposed to offer primary protection to the grid, although, at the expense of costs and losses. Alternatively, the Half-Bridge (HB) SM could be used as a primary protective device because of its commercial viability but it must be supported by a secondary protection since it has reduced fault blocking voltage capability [11][12][13].

Considering the fault blocking voltage capability of the HBSMs, it can be time consuming to resolve a blackout. Therefore, to integrate a backup protection strategy with an MMC to detect, locate and isolate the DC faults, while realizing the continuous operation of a healthy system is a current research issue.

Current backup protection schemes such as travelling and non-travelling wave types [14] [15] [16] rely on data from two sources, which are the inverter and rectifier ends. This causes a reduction in the accuracy of the data as it flows through the communication channel since they might be prone to delay, packet loss and wave reflections [17], thereby affecting the scheme selectivity and sensitivity to fault estimation [18]-[19]. In addition, the schemes suffer from setting manual protective thresholds [16].

Given the above shortcomings, research attention has been placed on artificial intelligence (AI) algorithms for backup protection. Table 1 presents current AI algorithms and their challenges. It has been shown that they suffer from sizeable computational burdens and misclassifications which weakens the accuracy of the fault isolation process [20]. These shortcomings result from the large amount of data used for training and testing the system [21].

To overcome the shortcomings of previous approaches, an intelligent fault localisation scheme using QSVM and GPR based on AI is proposed to utilize data from a single source. This backup scheme eliminates the need for a communication channel. Further, it also reduces the challenges of large dataset computational burdens by reducing data dimensions using signal processing techniques, before classifying and localizing faults. The proposed system is described in Section II, before being verified through simulation in Section III.

Table 1: Comparison of various AI Techniques for backup protection of MMC

AI Fault Location Methods	**Challenges**	**Sources**
Linear Discriminant Analysis (LDA)	LDA suffers from misclassification and its algorithm is synchronised with significant calculation burden.	[22] [23]
K-means data	This approach is slow because the standard deviation of the sampled signals is not discretized and filtered. Also, the K-means algorithm is sensitive to resistance, and the computational burden is enormous.	[24] [25]
Fuzzy Logic	The fuzzy logic derivation relies on human interpretation of system dynamics. They also experience a delay when tuning fuzzy system parameters in complex grid systems.	[14] [26]
Bayesian Networks	The algorithm suffers from significant computational burden which tends to slow their operation	[27] [28]
Neural Networks	Its performance may be influenced by weight adaptation algorithms, noisy data, and implicit data representation. The many layers used in its network may leads to many training cycles and computational burden when dealing with complex grid systems.	[29] [30] [31] [32]

II. THE PROPOSED PROTECTION SCHEME

The proposed scheme will be applied to a bipolar HBSM based MT-HVDC grid. It comprises four stages, starting from detecting fault current and voltage signals, signal processing of the fault samples, classifying the fault samples using QSVM and, finally, locating the fault impact point on the transmission line using GPR. These four stages are necessary to ensure accurate fault localization. Each are described in Sections II A to D.

A. Fault Detection

Fault detection is performed using intelligent device such as protective relays installed at both rectifier and inverter end of the transmission line.

Initially, current and voltage waveforms are sampled, generating a large raw dataset. From this dataset, impedances can be calculated.

The apparent impedance obtained by the relay prior to a fault is the pre-fault impedance and it is the ratio of measured voltage to current as shown.

$$Z = \frac{V}{I} = Z + Z \tag{1}$$

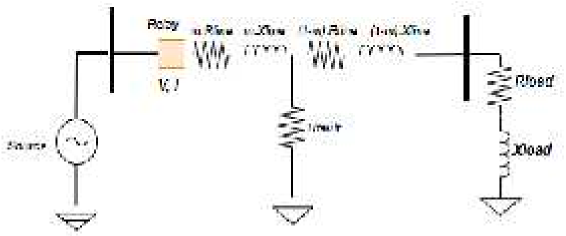

Fig. 1. Equivalent circuit parameter of a Transmission line during fault.

The DC fault impedance can be extracted by obtaining the Thevenin equivalent impedance of the circuit,

$$Z = \frac{(Z + [(1-m)Z])R}{(Z + [(1-m)Z]) + R\}} + m \tag{2}$$

(2) can be simplified if $R \gg R$ to,

$$Z = R + m \tag{3}$$

Where, m is the ratio of the fault distance to the total line distance while the normal operating impedance of the grid is the pre-fault impedance. A fault detection signal is generated as the impedance of the circuit falls below the pre-fault impedance. The collected fault samples exist as a large raw dataset awaiting processing. Dataset signal processing is described in Section II B.

B. Signal Processing

The large dataset of fault voltage and current samples is processed to extract important information. Signal processing entails reducing the calculation burden by extracting the prominent features in the fault samples, lowering the dimensional size of the fault samples and preparing the dataset for classification. The stages involved include the use of discrete wavelet transforms (DWT) and principal component analysis.

The DWT is a signal processing technique to decompose and categorize signals according to frequency. This allows fault signal transients to be easily extracted. The DWT can be obtained using:

$$D(m,k) = \frac{1}{\sqrt{u_0^m}}\left(\sum x[t]\Psi^*\left[\frac{k-nb_0u_0^m}{u_0^j}\right]\right) \tag{4}$$

And

$$\Psi m,k(t) = \frac{1}{\sqrt{u_0^m}}\Psi^*\left[\frac{k-nb_0u_0^m}{u_0^m}\right] \tag{5}$$

Where u_0 indicates the scale parameter, b_0 is the shift coefficient and $\Psi m,k(t)$ denotes the scaling function. The current and voltage transient signals from the DWT will be acted upon by principal component analysis (PCA).

PCA is a comprehension tool for mapping signals from high dimensional space to low dimension subspace thereby reducing the dimensionality without losing information contained in the dataset. For this paper, the feature selection was done using the PCA algorithm available on MATLAB.

From the wavelet theory, the lower-dimensional current and voltage samples can be obtained from wavelet energies,

$$E_j = \sum_k \left| L_j(k) \right|^2 \quad (j = 1,2,3,\dots,N) \tag{6}$$

Where, $L_j(k)$ is the coefficient of DWT

$$E_N(j) = \frac{E_j - m\ (M_K)}{s\ (k)}, f\ \ k \in \{I\ a\ \ V\} \ \&\ j = 1{:}N \tag{7}$$

$$m\ \ (M_K) = \frac{1}{N}\sum_{i=1}^{N} E_j \tag{8}$$

$$s\ (k) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_j - M_K\right)^2} \tag{9}$$

Where, E_N is the normalized transient currents and voltages dataset which is the desired input to the QSVM classifier.

C. Quadratic Support Vector Machine (QSVM)

The QSVM identifies the faulty transmission line in the network. It generates an optimal plane that separates the different fault samples into distinct regions to aid classification. Using a bipolar network, three different regions were created. Considering Fig. 2, SVM_1 represents the region for positive pole to ground fault, SVM_2 is for the negative pole to ground fault while SVM_3 is for the positive pole to negative pole fault.

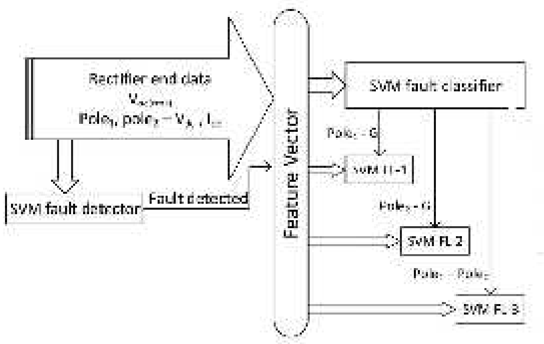

Fig. 2. Proposed SVM classifier

The SVM classifier categorizes the fault samples into different regions of the transmission lines by selecting the plane with the highest margin among the samples in the dataset. The constraints obtained are,

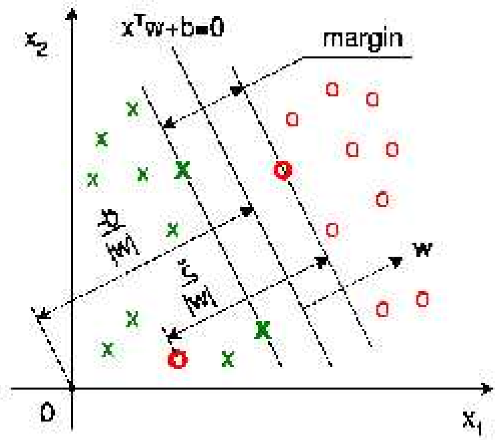

Fig. 3. 2-D SVM Classification

$$x_i^T \omega + b \geq 1 - \xi_i\ f\ \ \ y_1 = 1, \tag{10}$$

$$x_i^T \omega + b \leq -1 + \xi_i\ f\ \ \ y_1 = -1, \tag{11}$$

Combining the two constraints gives,

$$y_1(x_i^T \omega + b) \geq 1 - \xi_i \quad \text{for } \xi_i \geq 0 \tag{12}$$

The equation gives the highest possible margin for linearly separable samples. To generate the different support vectors, (12) will be substituted into the Lagrange function,

$$L_P = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}\xi_i - \sum_{i=1}^{N}\alpha_i\{y_i(x_i^T\omega + b) - 1 + \xi_i\} - \sum_{i=1}^{N}\mu_i\xi_i \tag{13}$$

Where, ξ_i is the measure of misclassification of the samples while α_i and μ_i are the Lagrange multipliers. The SVMs will be obtained by maximizing the separations between the different regions using the Lagrange function.

$$m\ \ \ L(\alpha) = \sum_{i=1}^{N}\alpha_i - 2^{-1}\sum_{i=1}^{N}\sum_{i=1}^{N}\alpha_i\alpha_j y_i y_j k(x_i, x_j) \tag{14}$$

$$\text{Subject to } \sum_{i=1}^{N}\alpha_i y_i = 0 \tag{15}$$

and

$$\alpha_i \geq 0 \tag{16}$$

Once the optimization function is solved, the fault samples with training points of $\alpha_i \geq 0$ are the SVMs.

After each region has been identified, if a positive pole to ground fault occurs, SVM_1 will display +1 while negative pole to ground and pole to pole faults will display -1. Hence, the positive pole to ground path will be the focal point for the gaussian process regressor in locating the exact point of fault impact on the transmission line.

D. Gaussian Process Regression (GPR) with Squared Exponential Kernel

This algorithm will localize the fault on the grid for ease of isolation.

From linear regression,

$$y = m\ \ + c \tag{17}$$

$$y = \xi(x) + f(x) = x^T \alpha \tag{18}$$

Where y is the response variable from the fault dataset, x is the normalized fault voltage and current from the PCA and ξ is the additive noise.
The GPR model uses the mean and covariance function to determine the fault position.

Mean $\delta(x) = E\{f(x)\}$ and the covariance which measures the fault location on the fault path is,

$$V(x_i, x_j|\Phi) = \delta_f^2 e \left(\frac{-\gamma}{\delta_L^2}\right) \tag{19}$$

The trained fault dataset is $(x_i, x_j|\Phi)$

$$\gamma = \sqrt{(x_i - x_j)^T (x_i - x_j)} \tag{20}$$

$$\Phi = \{\delta_L = m \quad (S \quad (x));\ \delta_f = S \quad (y)/S \quad (2)\} \tag{21}$$

Where, γ is the Euclidean distance to the fault location and Φ is the unconstrained parameterization vector.
For this study, the GPR location processes will be performed using the machine learning app on MATLAB.

III. Simulation, Results and Discussion

The system modelling and fault dataset were obtained using PSCAD. The system design specifications are presented in Table 2.

Table 2. System Design Specifications

System Parameter	Values
Transmission line	±500 kV, 1000 km
Fault distance from inverter relay	From 20 km to 980 km
Fault inception angle (degrees)	0, 30, 60, 90
Fault resistance (Ω)	0.02, 40, 180, 350
Smoothing reactor	5 mH at both ends

The simulation was done at a sampling frequency of 2 kHz with a solution step of 6 microseconds. Fig. 4 shows the schematic of the bipolar network.

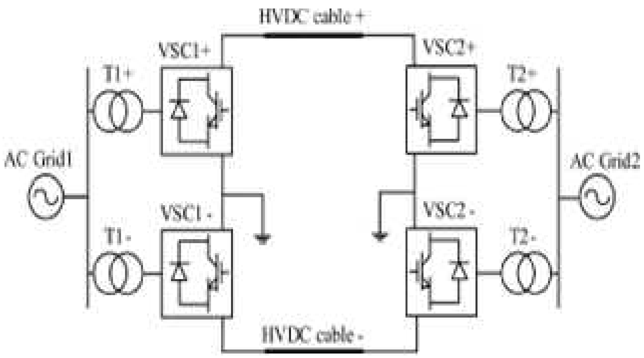

Fig. 4. Bipolar MMC HVDC Network

For this research, the fault current and voltage dataset signals were generated by varying the system tunable parameter at different locations of the fault, inception angles and fault resistances. A total of 23520 samples were collected.

Fig. 5 presents the accuracy of the QSVM classifier while Fig. 6 gives a comparison for different machine learning classifiers. It shows that QSVM is highly efficient for classifying MMC based HVDC fault with an accuracy of 97.5 %. The accuracy of the SVM would benefit the overall network such that the exact region of the transmission line where the fault is occurring could be quickly identified for faster signals to be sent to the CBs managing the path.

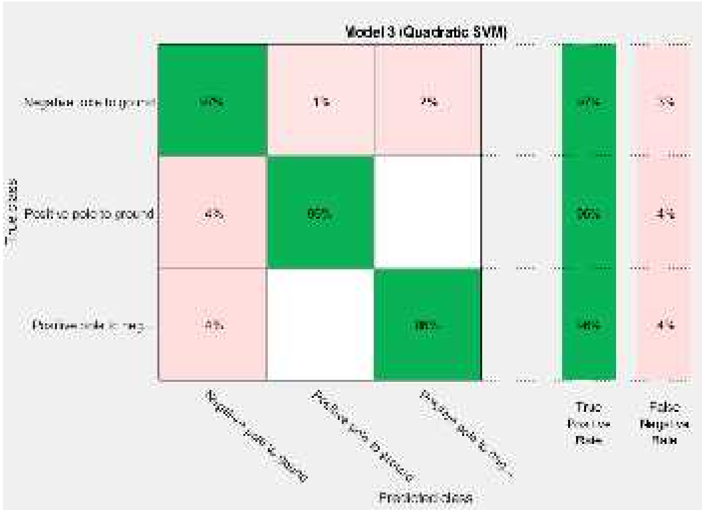

Fig. 5. Confusion matrix from the SVM classifiers

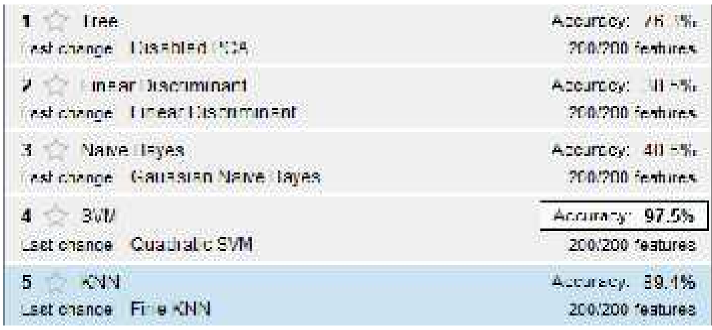

Fig. 6. Comparison among the various ML classifiers

The same current and voltage signals used for classification were used for fault localization, and the fault was simulated at every interval of 2 km on the line. Fig. 7 presents the line of best fit between the different fault samples and possible locations. The dotted points are the normalized fault samples generated, while the exact location of fault impact point was obtained by tracing the sampled fault signal to the line of best fit.

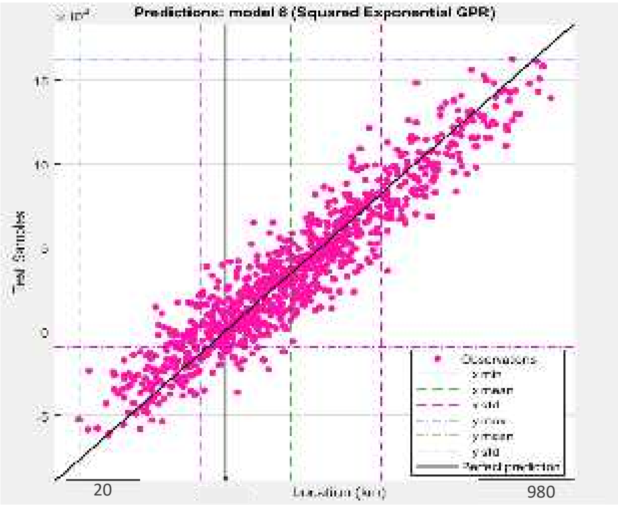

Fig. 7. Fault distance versus fault signals using Squared Exponential GPR

The graph below gives the comparison between the simulated location and the actual location of the fault impact point to verify the accuracy of the backup protection techniques.

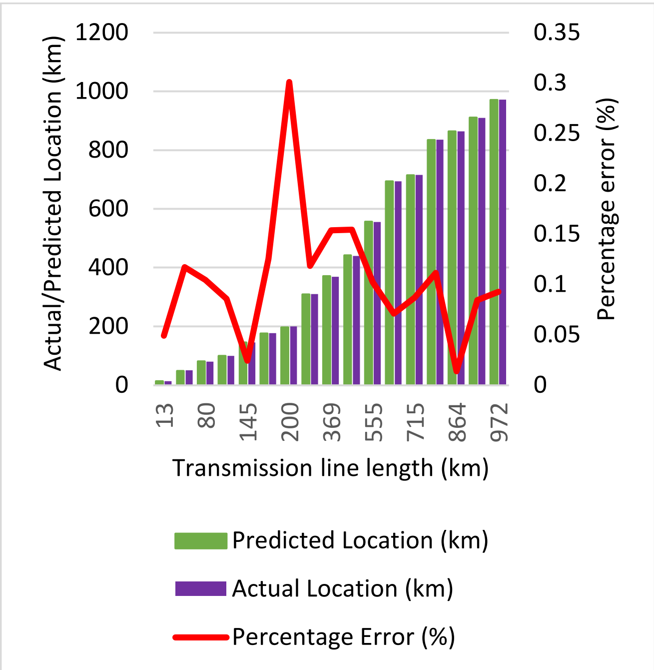

Fig. 8. Fault Location Estimation for Positive Pole to Ground Fault

From this graph, the purple bar shows the actual location, and the green bar shows the predicted location. Close agreement exists between the actual and predicted fault locations, as evident from the percentage errors given in Fig. 8.

IV Conclusion

In this study, QSVM and GPR backup protection scheme were applied to a bipolar HVDC network, to promote FRT. The simulation of the MMC was done using PSCAD while the processing, testing, and training of the fault current and voltage samples was done using MATLAB. The large dataset of fault samples generated was processed to overcome the challenges of computation burden which affects the speed and accuracy of the fault localization process. In addition, the scheme requires data from a single source (Rectifier-end) which proves to be very efficient in eliminate the drawbacks of using a communication channel for data collection. Considering the prediction of the fault impact point, it was observed that the mean error in percentage was about 0.02% which is fair enough. Future contribution will entail the use of QSVM and GPR backup protection scheme on more complex multi-terminal HVDC grid. In addition, real time simulation will be performed to verify its timeliness (i.e whether it can act fast enough).

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