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DC ARC FAULT LOCATION IN VSC-HVDC SYSTEMS BASED ON DEEP LEARNING USING PMU

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In the presented paper, a method for locating DC arc fault in VSC-HVDC transmission lines is proposed. Additionally, wavelet transform from advanced techniques of signal processing is employed for the purpose of extracting important characteristics of fault signal from both sides of the line by PMU. To do so, Deep learning is used to identify the relation between the extracted features from wavelet analysis of the fault current and variations under fault conditions. In this method, there is no need to know about the line information. Using the intelligent method also reduces the calculation complexity. Studies and simulations are done by implementation on a 50 kV VSC-HVDC transmission line with 25 km length in Matlab. Obtained results demonstrate the high precision of the presented method with the maximum fault value of 3%.

Keywords: DC Arc Fault, Fault Location, VSC-HVDC Lines, Deep Learning, Wavelet Analysis, Phasor Measurement Units (PMU)

1. Introduction

Nowadays, considering the improvements achieved in power electronics equipment, using HDVC transmission lines in overhead lines and underground cables is increased significantly [1-2]. Fast and reliable control are features of these systems. Additionally, HDVC systems can be used to connect asynchronous networks [3-5]. Nevertheless, the main issue in using this form of lines, is their protection. Finding the fault location is of quick servicing and important diagnosing aspects. Precise fault location helps with determining the weaknesses of transmission line and forming a desirable adaption to decrease the fault occurrence probability in these locations.

DC arc faults are one of common problems of HVDC transmission lines. Non-permanent DC arc faults on VSC-HVDC transmission lines should be located to avoid power outages immediately due to destructive effects of DC arcs. According to DC arc characteristics, high magnitude of current has destructive effect on both side converters and inverters and finding location of DC arc faults is difficult by previous methods [6].

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Generally, fault location in line methods divide into intelligent network methods [7-10] and classic analytic methods [11-13]. In recent years, the intelligent network-oriented methods have attracted a lot of attention due to more simple calculations and high flexibility capabilities in learning. Currently, protection techniques of HVDC systems fall into three categories of: travelling wave protection [14-16], signal procession, and machine learning [17-18]. For the purpose of internal and external fault recognition on HVDC line, travelling wave protection is used in [14]. For the same purpose, fault impedance and high frequency components are used in [16]. In [17], entropy and wavelet transform are used to protect HVDC systems. In [18], an algorithm is presented to locate the fault based on neural network.

As mentioned before, currently, intelligent methods are dominant in non-linear and complex problems. In this regard, studies based on intelligent methods have been investigated in the field of locating fault in transmission lines [19-21]. In [19], a method is proposed to find the fault location in 4-circuits transmission lines based on adaptive neural-fuzzy inference system (ANFIS). Finding the location of fault in transmission line is addressed in [20] by using support vector machine. It must be considered that one of the most used intelligent methods currently is Deep Learning [21] which is of high precision in determining the desired target. Due to novelty of improvements of this algorithm, limited works are done in protection of power systems by Deep Learning which are proved to be of high precision [22-23]. In [22], identifying the type of arc fault in transmission system which are hard to recognize by using other algorithms is addressed. It must be considered that in the methods based on learning, choosing the most desirable characteristics is of great essence for the methods. Hence, identifying the features related to location of fault can help significantly in improving the precision of the deployed algorithm [10] that Deep Learning do this task properly.

In the presented method, characteristics extracted from fault current is of great importance. The extracted features behavior is directly related to the parameters of fault such as location, resistance and inception, in a way that the variations, affect the extracted features [24].

Here, a method based on wavelet analyzes by using Deep Learning to determine the location of DC arc fault in VSC-HVDC transmission lines is presented. Using phasor measurement units (PMU), the fault current signal of both sides of the line are obtained and their important features are extracted by the wavelet analyzes. The main reasons of using PMU is getting synchronized and precise data from both sides. The obtained features are as entry data of the Deep Learning algorithm. The reason of using the data of both sides of the line is the dependence of this algorithm on great information of fault current signal as entries and increasing the precision of the presented algorithm.

In this paper, simulations are implemented in Matlab with having considered a 50 kV VSC-HVDC transmission line with 25 km length. The DC arc fault is studied in terms of fault inception and fault location. In the presented method, PMU is used to obtain the information, which is capable of handling the synchronization problem, and the high precision sampling challenge. High speed in determining the DC arc fault location, reducing the calculation complexities, independency of knowing the line parameters, and high precision are some of the advantages of the presented method. The maximum error percentage of this method is below 3%.

2. Wavelet Analysis

Wavelet Analysis used the multi-resolution analysis (MRA) to decompose the signal into high and low frequency bands in order to evaluate the signal partially and approximately [25-26]. Many researches use the MRA to analyze the locating fault in transmission lines [27-28]. The presented method is focused on extracting features of 3-phase current signals of both ends during the fault occurrence in 1000-2000 frequency spectrum. These features include transient fault features to evaluate the signal details and determine the fault location. The process of MRA of an entry signal is depicted in Fig. (1).

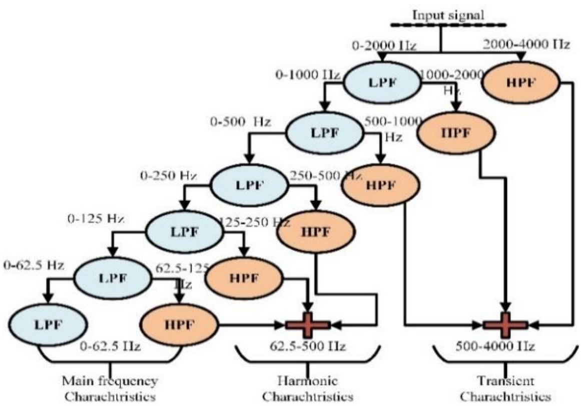

Fig. 1. Frequency division of MRA [19]

A brief explanation of the wavelet transform is given below:
The Continuous Wavelet Transform *(CWT)* is expressed as:

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

X (t) is input signal, *φ (t)* is the mother wavelet and $\varphi_{a.b}(t) = \frac{1}{\sqrt{|a|}}\varphi\left(\frac{t-b}{a}\right)$ are transferred and detailed versions. Constants a and b are respectively contraction and transfer constants. *CWT (x, a, b)* is the wavelet transform of signal x with contraction *a* and transfer (time shift) *b*. CWTs present the time-frequency various information.

Discrete wavelet transform (DWT) is a digital counterpart known of CWT which is used in the proposed method. DWT of a signal is expressed as [28]:

$$DWT(x,m,n) = \frac{1}{\sqrt{a_o^m}} \sum_t x(k) \varphi \left(\frac{n - l a_o^m}{a_o^m} \right) \tag{2}$$

Parameters *a* and *b* are substituted with a_0^m and la_0^m.

DWT decomposes a signal into different levels of approximate (a_1, a_2… a_n) and details (d_1, d_2... d_n). A signal decomposes through high pass, and low pass filters in time domain.

The information obtained from the wavelet Analysis give useful clues in order to find location of the fault. In this paper, the current signal in time domain is obtained for various fault situations from both sides of the VSC-HVDC lines, and are analyzed with wavelet Analysis. The Daubechies wavelet (DB4) is used as the mother wavelet due to its suitable operation in fault analysis in power systems [27-28].

In this paper, 1 KHz is as sampling rate. Among the presented coefficients of various decomposed levels, the set of coefficients of 1000-2000 HZ is the only one considered. The d_2 (details coefficients) supports necessary transient features for the proposed method.

3. Phasor measurement units (PMU)

Phasor measurement units have become one of the important elements in wide area measuring systems for monitoring, protecting, and advanced practical controlling of power systems. PMUs address the synchronous measuring of current, and voltage phasors in real time. Synchronization is achievable by synchronous sampling of current, and voltage waveforms by using time signal of the GPS. Synchronizing the measured phasor is the reason for rising of a new level of monitoring, protection, and practical control [29].

The PMU technology gives in the phasor information (the magnitude and the angle) in real time. Citation to inclusive reference time to submit the transient features of the power system is one of the advantages of the phase angle. This technology positively affects the learning of the real time behavior of the power system. Considering the improvements in this technology, the microprocessor equipment such as protection relays and Disturbance Fault Recorders (DFRS) combined with sample PMUs, are also of the extended features.

To achieve the synchronous measuring of phasors in a wide power system, synchronization is needed. Meaning that all phasor measuring for the same time are synchronous. High resolution of 60 sample per cycle, measuring the phase angle, and observability of dynamic states are some of the advantages of phasor measurement units.

4. Deep learning

Deep learning is the machine learning in a way [21] that its entries are the main data that extract the important features in a multi-layer structure and learn and achieve the specific goal in the end.

A neural network has *n* layers. The forward network topology is shown in Fig. (2). The forward deep network is a form of deep learning in a way that f(x) match $f^*(x)$. For the learning data, each entry is tagged with y=f*(x) and products the $f^*(x)$ value. For the purpose of learning, a function described as below is used:

$$\hat{y} = f(x;\theta) \tag{3}$$

The algorithm must learn how to generate the desirable output from the learning data. The neural network learning is based on the minimum of the waste function. Hence, the difference between the real output and the desirable one must be at the minimum. Deep Learning designs a plan to classify the tasks that leads to massive learning of the learning data of a network, and classification of the entry data. The network depth reveals that the hidden layers of a network are able to extract various features. Deeper networks have more complex data [22].

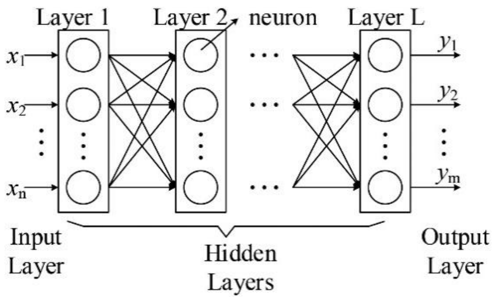

Fig 2. Feed forward network [21]

5. DC arc fault model

Van and Warrington presented a model based on different tests on HV ac systems for arcing current varies from 100 to 1000 A and several electrode distance [30].

The *V –I* characteristic of a stable arc was determined as

$$V_{arc} = \frac{8750L}{I_{arc}^{0.4}} \tag{6}$$

Where, *L* is the arc length in feet.

6. The proposed method

The algorithm of the proposed method has two levels which are procession of the entry data and precise recognition of the fault location respectively. Fig. (3) demonstrates the flowchart of the presented algorithm. 3-phase fault current of both sides of VSC-HVDC line is obtained and wavelet analysis is applied to it. Coefficients of the second level details, named as S_a , S_b, and S_c, of the 3-phase fault current signal *a*, *b*, and *c* of both sides of the line are used as the Deep Learning algorithm entries, to identify type of fault and locate the fault.

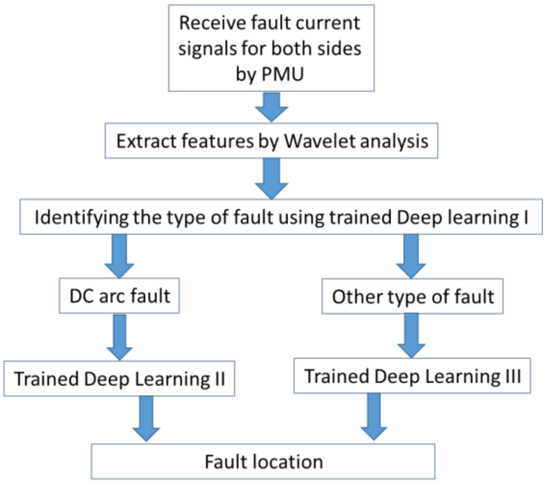

Fig. 3. The flowchart of the presented algorithm

The entry data are processed as below:

First, fault current is obtained from phasor measurement units of both sides of the line. Second, to decompose current signal, wavelets are used. Eventually, the coefficients of the second level details, S_a , S_b, and S_c, are selected as entry data of Deep Learning.

6.1. Locating fault in VSC-HVDC lines

The features extracted are the entries of the Deep Learning network. The normalized value of the coefficients of the second level details, named: S_a, S_b, and S_c of 3-phase fault currents of *a*, *b*, and *c* are used as the entries of the Deep Learning algorithm. The entries of this network are S_a, S_b, and S_c, and its output (D) is fault location.

To design the best Deep Learning network, it's precisely and efficiently learning is necessary. The learning must be done in such way that various situations of the fault resistance, fault location, and fault inception be assumed. Functionality of the Deep Learning network is evaluated by the test data different from training data.

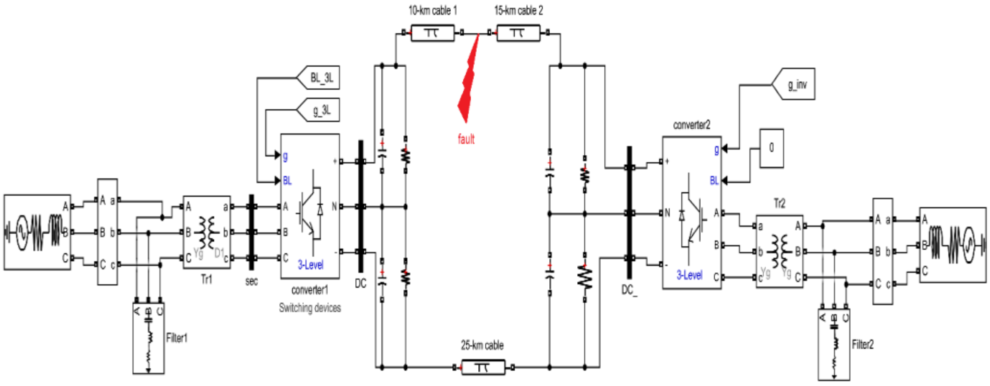

Fig. 4. The Simulink of study case

7. Simulations

Simulations are run in Matlab Simulink (Fig. 4). To implement the wavelet analysis and the Deep Learning network, Matlab is employed. The test and learning algorithms are generated from variations in fault such as location, resistance and inception.

These situations are included in tables (1) and (2) for the learning and test of algorithm respectively.

Table 1.

Training data

Fault Location	10% to 90% of the line length, with step 5%
pole	+ pole, -pole
Fault Inception(degree)	2.5, 12, 24, 36, 72, 108, 131, 153, 169, 175.5
Fault Resistance (Ω)	1, 10, 20, 30

Table 2.

Test data

Fault Location	10 Random places
pole	+ pole, -pole
Fault Inception(degree)	6, 48, 90, 120, 145.5, 173.25
Fault Resistance (Ω)	2, 9, 18, 25

According to Figs. (5) and (6), the second frequency level is considered to generate the input algorithms. With implement the wavelet transforms on the fault current signal from the two sides of VSC-HVDC line, each pattern includes 320 features. The sampling rate is selected 1 kHz for simulations, and Db4 is used as the mother wavelet. The frequency band of the second level of details includes 1000-2000 frequencies. It yields transient features such as fault in power systems.

As shown in the table (1), trained data are 1280 pattern, and according to the table (2), tested data are 480 pattern.

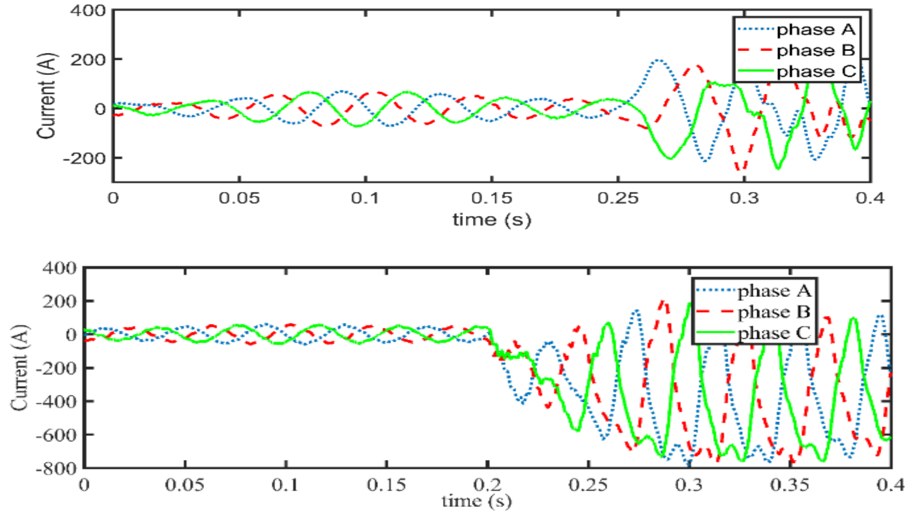

Fig. 5. Three-phase current signals of both sides measured by PMU under the fault at 10 km. (a. current signal of sending end, b. current signal of receiving end)

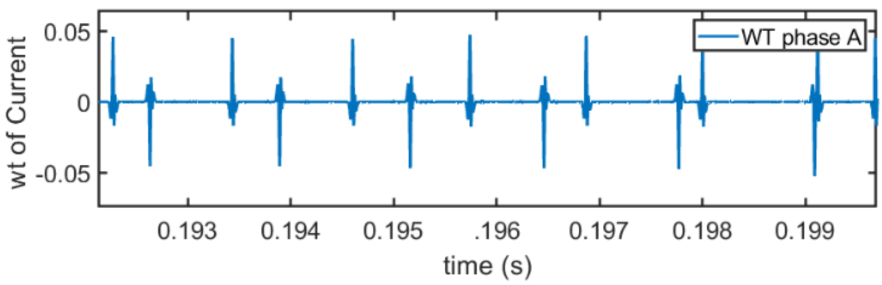

Fig. 6. Wavelet of fault current at a distance of 10 km from sending end having fault inception angle of 40 and fault resistance of 1 ohm

8. Results and Discussion

Fault is occurred with various situations of the fault resistance, fault location, and fault inception. Values of coefficients of the second level details S_a, S_b, and S_c are considered as the entries of the Deep Learning algorithm, and location of fault is considered as the output. The Deep Learning network has taught the functions to decrease error of the fault location.

To evaluate the precision of the presented method in calculating location of fault, the proposed method has been tested under various fault situations. Considering the obtained results, it can be concluded that the algorithm is of acceptable precision in protection of VSC-HVDC lines. The functionality of precise fault locating by using the Deep Learning network is tested and included in tables (3) to (5). The error percentage is defined as below:

$$\%Error = \frac{|Estimated\ location - Actual\ Fault\ Location|}{Total\ Length} \times 100 \tag{4}$$

To evaluate the sensitivity of the presented method, fault is occurred under various conditions such as location, inception, and resistance. In tables (3) to (5), the sensitivity of algorithm is investigated.

The sensitivity of fault location is shown in table (3). Each fault point has 48 pattern. With evaluating the obtained results in table (3), it can be deduced that the proposed method is of sufficient precision considering the fact that the test condition is different from the learning conditions. All entries of the test network has average error value equal 0.773%, and the maximum error is 2.336 %.

Table 3.

Results of fault locating for various Fault Distance

Fault Location (Km)	Min error (%)	Max error (%)	Average error (%)
1.2	0.175	2.336	0.863
3.3	0.106	1.325	0.786
4.8	0.114	1.685	0.925
7.1	0.085	0.582	0.482
9.6	0.203	3.635	0.615
10.8	0.235	1.352	0.789
13.9	0.005	2.036	0.986
16.7	0.015	1.445	0.833
19.6	0.192	1.368	0.546
21.7	0.116	2.065	0.911
Mean of All	0.124	1.782	0.773

It is assumed in the presented method that the fault impedance is purely resistance. For evaluating the sensitivity of the proposed method to fault resistance, fault for different fault resistances is given in Table (4).

Table 4.

The algorithm sensitivity under variations of Fault Resistance

Fault Resistance (Ω)	Min error (%)	Max error (%)	Average error (%)
2	0.13	1.453	0.783
9	0.22	1.362	0.632
18	0.18	1.883	0.836
25	0.63	2.163	1.036

The evaluated maximum fault is 2.163% and evaluated fault average is 0.82% for all modes. Clearly, complex fault impedance affects the precision of the algorithm negatively. Nevertheless, the method obtained results of sufficient precision. It can be seen from table (4) that the maximum observed fault occurs for 25 Ω. For this resistance, the average observed fault is only 1.036%.

To demonstrate the effect of fault inception, fault is applied for constant location with constant resistance value for different initial angles. Maximum and average evaluated fault for each fault for different fault inception is shown in table (5). As shown, the fault location precision is still acceptable despite variation in fault inception.

Fault location method for fault inception close to point passing the current zero is studied. Some of test patterns are generated based on fault inception of 2.25 and 177.75. Other situations are proposed to generate test data based on table (2).

Average and maximum obtained fault for fault inception of 2.25 are 1.05 % and 2.12 % respectively. Additionally, the mentioned values are 1.31 % and

3.48 % for fault inception of 177.25. Therefore, proximity of the points to the current zero when fault is occurring, affects in reducing the precision of the presented method. If the distance of the fault inception form the zero point is less than 2.25, the proposed method does not function properly. In general, the method has desirable functionality only in 97.5% of the times.

Table 5.

The algorithm sensitivity under variations of Fault Inception Angles

Fault Inception (degree)	Min error (%)	Max error (%)	Average error (%)
6	0.163	1.145	0.889
48	0.059	1.065	0.736
90	0.116	1.966	0.926
120	0.358	1.348	0.916
145.5	0.605	1.054	1.023
173.25	0.993	2.366	1.315

In accordance with the obtained results from the tables, it can be observed that the presented algorithm is of acceptable precision in determining the fault location in VSC-HVDC lines. The algorithm determines the precise location of fault in most cases and keeps the algorithm fault under 3%.

9. Conclusion

In this paper, a method to locate the DC arc and other type of fault in VSC-HVDC transmission lines is proposed. The proposed algorithm includes two levels to extract the features and locate the fault. Wavelet MRA has been used along the Deep Learning network in order to achieve this goal.

The proposed algorithm is different from the conventional ones that are proposed to protect the transmission lines based on heavy and complex calculations. To extract the important features and obtain the exact fault location, the wavelet transforms, and intelligent calculation techniques of the Deep Learning network are used. In presented method, for checking the sensitivity of the proposed method, fault is evaluating under various conditions. The simulation results show that the algorithm is a fast, precise, and reliable to finding the location of fault. This method is able to handle synchronization of the information obtained from the two sides of the line by using PMU.

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