Computational Research Progress in Applied Science & Engineering

ISSN 2423-4591

CRPASE Vol. 05(04), 98-104, December 2019

A Hybrid Method for Fault Location on VSC-HVDC System Using ANFIS with New Training Algorithm and Hilbert-Huang Transform

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Keywords

VSC-HVDC,
Feature extraction,
Fault location,
ANFIS,
aABC algorithm.

Abstract

High-voltage direct current (HVDC) system is a highly efficient alternative for transmitting large amounts of electricity over long distances and for special purpose applications. As a key enabler in the future energy system based on renewables, HVDC is truly shaping the grid of the future. Designing an accurate and fast fault location method in HVDC system is necessary to maintain uninterrupted power delivery and protect sensitive devices of these systems. This paper presents a hybrid method for locating fault on voltage source converter HVDC (VSC-HVDC) transmission line using one terminal current data. The proposed method includes three main modules: the feature extraction module, the estimator module and training module. In the feature extraction module, Hilbert-Huang Transform (HHT) is used to frequency, time and energy domain feature extraction. The extracted features are time delay, characteristic frequency, energy attenuation and high-frequency energy. In the second module, Adaptive Neuro-Fuzzy Inference System (ANFIS) is used as an intelligent estimator. In ANFIS, antecedent and conclusion parameters have vital role on ANFIS performance. Therefor in training module, Adaptive and Hybrid Artificial Bee Colony (aABC) algorithm are used to train the ANFIS. The proposed method is tested on 250 km VSC-HVDC transmission line and the obtained results have shown that a combination of new features and optimized ANFIS has high accuracy in fault location in HVDC systems.

1. Introduction

High voltage direct current (HVDC) transmission is an economic way for long distance bulk power delivery and/or interconnection of asynchronous system with different frequency. HVDC system plays much more important role in power grids due to their huge capacity and capability of long distance transmission. The development of power semiconductors devices, especially IGBT's has led to the transmission of power based on voltage source converters (VSC). The VSC based HVDC (VSC-HVDC) installation has several advantages compared to conventional HVDC such as, independent control of active and reactive power, dynamic voltage support at the converter bus for enhancing stability possibility to feed to weak AC systems or even passive loads, reversal of power without changing the polarity of dc voltage (advantageous in multi terminal dc system) and no requirements or fast communication between the two converter stations [1-3].

The VSC-HVDC will find wide applications in the fields of new energy (such as wind farm), island power supply, and renovation of urban power grids and so on [4]. However the fault-location of VSC-HVDC transmission lines is an extremely tough job due to long lines, severe weather condition and varied topography. Therefore, it's of great significance to vigorously develop fault-location techniques for VSC-HVDC transmission lines [5].

Currently, the methods of fault location on VSC-HVDC transmission lines normally utilize traveling-wave to get fault distance. While the other methods mostly need to know specific parameters of transmission lines. For the traveling-wave fault-locating theory [6, 7], it has highest precision and has been applied in practice. Then, by knowing traveling wave-head arrival time detected from the opposite bus and wave velocity, the fault distance is able to be identified. However, signal from the global positioning system may be lost, thus the fault-location under unsynchronized two-end measurement requires further research. The researchers reset zero time reference point and mix the traveling wave theory with the Bergeron time domain for fault location [8]. But this approach still requires lines parameters such as reactance, resistance and suseptence. The natural frequency of the fault signal is related to the fault distance [9], however this method for fault location needs to pick up the precise frequency and

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Received: 12 October 2019; Accepted: 18 December 2019

the wave speed. This method leads to heavy comouatations and long running time.

The resonant characteristics of DC capacitance are exploited in the HVDC fault location [10], while there are dead zones in the application. A novel method based on double measurement points [11] still has the problem of fault resistance. Recently, the intelligent algorithm was widely used in all aspects of the power system. In the field of fault location, it is able to refrain the deviation by evaluating the lines parameters. To improve the accuracy of model, various approaches capture different fault features to train the model [12–15]. Energy percentage in each level is utilized for training the artificial neural network and the energy information is provided by wavelet multiresolution analysis of the recorded transient voltage signals [12]. The features of the traveling wave can be extracted from the voltage and current by using wavelet packet decomposition (WPD) algorithm. And they are as the input vectors of RBF (radial basis function) neural network [13]. These methods extract features by the wavelet.

Another new approach is posed based on hyperbolic S-transform and the authors yield the change in energy and standard deviation to achieve fault location via RBF neural network [14]. Moreover, singular value decomposition (SVD) method can also be used for extracting the features of HVDC traveling wave [15]. On the other hand, the classifier (support vector machine, SVM) and regression (SVR) schemes have been trained with features and have favorable performance in the application of intelligent algorithm.

Based on the published papers about the fault location in VSC-HVDC systems, there are some facts which should be considered during the design of estimator. One of these issues is the feature extraction. Generally the features of fault location are divided into frequency domain and time domain. Grounded fault can be located utilizing the time difference delay of modal components [16], and the characteristic frequency for the location is proposed [17]. This paper proposes a new scheme of extracting features through synthetical consideration. Hilbert-Huang Transform (HHT) is a new non-stationary signal analysis method and it can also be considered as adaptive time–frequency analysis method. Its application to the transient signals from faulted power system is particularly advantageous. By using HHT algorithm, the time delay of different modal components and the information of frequency domain are used to train estimator.

Another issue is related to the choice of the estimation approach to be adopted. The developed method uses fuzzy rules for fault location. In the proposed method, an intelligent system has been developed which has fuzzy rules obtained by Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS uses a heuristic learning algorithm whose high performance has been proved in function approximation and estimation problems. Thus, proposed system has a strong inference engine containing fuzzy rules that can detect hidden relations in the case unrecognized by the human expert.

The rest of the paper is organized as follows. Section 2 describes the needed concepts, including the ANFIS and HHT. Section 3 describes the proposed system. Section 4 shows some simulation results and finally Section 5 concludes the paper.

2. Needed Concepts

The proposed method is composed based on HHT and ANFIS. In this section these needed concepts are introduced briefly.

2.1. Hilbert-Huang Transform

HHT is an alternative approach of time frequency analysis (TFA), which was developed by Huang et al. in 1995 [18]. This method was specially developed for analyzing non-linear and non-stationary data just like machining vibrations. Unlike the traditional signal analysis techniq ues like FFT, HHT can be used for unsteady and/or nonlinear vibration signals. And also, different from FFT method, HHT does not involve the concept of frequency resolution or time resolution, but introduces the concept of instantaneous frequency. Consequently, a uniform high resolution is obtained in the full frequency range in HHT [19].

HHT consists of two consecutive procedures; an empirical mode decomposition (EMD) and Hilbert transform. In EMD, an original signal is decomposed into a series of components called intrinsic mode functions (IMFs $= \{c_1, c_2, \dots\}$). In each IMF has individual mode oscillations, amplitude and frequency as function of time. Therefore, each IMF component has a physically meaningful.

The main steps of HHT are summarized as follows:

Step 1: Considering that we have any discrete data $x(t)$ whose length is N.

Step 2: All the local maxima and the local minima are connected with natural cubic spline lines to form the upper $u(t)$ and the lower $l(t)$ envelopes.

Step 3: In this step, compute the difference between the data and the mean envelope to get the proto-IMF h_i.

$$h_i = x(t) - \left(\frac{u(t) + l(t)}{2}\right) \tag{1}$$

Step 4: The $h(t)$ have to be checked against the stoppage criterion of IMF as expressed in Eq. (2) to determine if it is an IMF or not.

$$\sum_{i=1}^{N} \frac{[h_i - h_{i-1}]^2}{h_i^2} < SD \tag{2}$$

where h_i is the sifting result in the i-th iteration. SD is a threshold value.

Step 5: If h_i does not satisfy to the stoppage criterion of IMF, then, h_i is used as the new input data and iterate the steps 2–4, till h_i satisfies the stoppage criterion of IMF.

Step 6: After h_i fulfills the condition as expressed in Eq. (2), assign it as a component of IMF$c_j(t)$. And the residue $r(t)$ is defined as Eq. (3)

$$r(t) = x(t) - c_j(t) \tag{3}$$

Repeat the operation step 2–6 for extracting the next IMF using the new input data.

Step 7: The operation ends when the residue $r(t)$ contains no more than one extremum (monotonic residue). The output of EMD process is a set of IMF components

$c_j(t), (j = 1,2, \dots, N_k)$, where N_k is number of modes. In addition, the last mode $c_{Nk}(t)$ is a monotonic residue $r_{Nk}(t)$. The decomposition of the signal $x(t)$ into a set of IMF components $c_j(t)$ and a monotonic residue $r_{Nk}(t)$ can be achieved mathematically using Eq. (4)

$$c_j(t) + r_{Nk}(t) \tag{4}$$

The frequency components contained in each frequency band are different and they change with the variation of signal $x(t)$.

The second procedure is the Hilbert transform for all of IMF components to generate an energy-time-frequency distribution which is called as Hilbert spectrum. The Hilbert transform of each IMF $c_j(t)$ is defined as Eq. (5)

$$H(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{c_j(t)}{t-\tau} \tag{5}$$

With the Hilbert transform, the analytic signal is defined as Eq. (6)

$$Z(t) = c_j(t) + iy(t) = a(t)e^{i\emptyset(t)}$$

$$a(t) = \sqrt{c_j^2(t) + y^2(t)} \tag{6}$$

$$\emptyset(t) = tan^{-1}\left(\frac{y(t)}{c_j(t)}\right)$$

where $a(t)$ is the instantaneous amplitude and $\phi(t)$ is he phase function. The instantaneous frequency can be given as Eq. (7)

$$\omega(t) = \frac{d\emptyset(t)}{dt} \tag{7}$$

Applying the Hilbert transform to each IMF, and calculating the instantaneous frequency $\omega(t)$ to get a time–frequency distribution. The Hilbert transform can be expressed in the following form (Eq. (8)).

$$X(t) = \sum_{j=1}^{N_k} a_j(t) exp\left(i\int \omega_j(t)dt\right) \tag{8}$$

2.2. ANFIS

ANFIS is a fuzzy inference system implemented in the framework of adaptive networks that is presented and developed by Jang in 1993 [20]. The ANFIS utilizes the learning capability of the ANNs to extract the fuzzy $if \Rightarrow then$ rules with fitting membership functions (MF) worked out from the training input-output pairs, which in turn leads to the inference. Generally, ANFIS consists of two main parts including the antecedent part and the conclusion part. The antecedent and conclusion parts are interconnected through fuzzy rules within the network structure of ANFIS. ANFIS is trained and updated by using parameters found in these parts. Unknown parameters in the antecedent and conclusion parts must be determined using learning algorithm. More details regarding ANFIS can be found in [20].

3. Proposed Method

This paper presents a hybrid method for locating fault on VSC-HVDC transmission line using one terminal current data. The main contribution of this paper is a new fault-location algorithm on HVDC transmission lines. The proposed method is a single ended method which makes full use of the frequency, time and energy to capture the fault features. HHT algorithm accurately gets the time difference delay of modal components and the information of frequency with the instantaneous frequency analysis as well as boundary spectrum. In addition, considering diversification of energy the features are used as input of ANFIS. It is found that the time delay, characteristic frequency, high-frequency energy and the attenuation of energy are related with fault distance. The proposed method includes three main modules: the feature extraction module, the estimator module and training module. The main structure of proposed method is shown in Figure 1. In this method, adaptive and hybrid artificial bee colony (aABC) algorithm is used as the learning algorithm [21]. In the past decade, evolutionary algorithms have been used successfully in engineering problems [22-35].

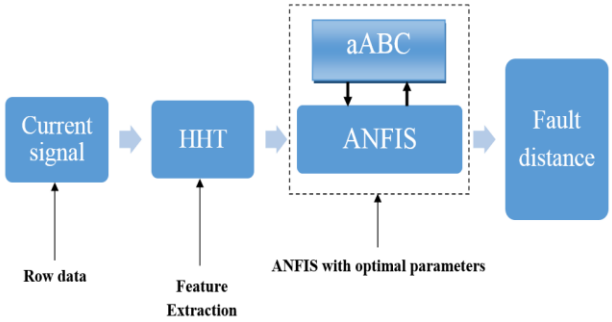

Figure 1. The main structure of proposed method

Figure 2 is the schematic diagram considering unipolar fault on VSC-HVDC. It is consisted of exchange station, AC filter, converter reactor, converter transformers, DC capacitor and DC lines, etc.

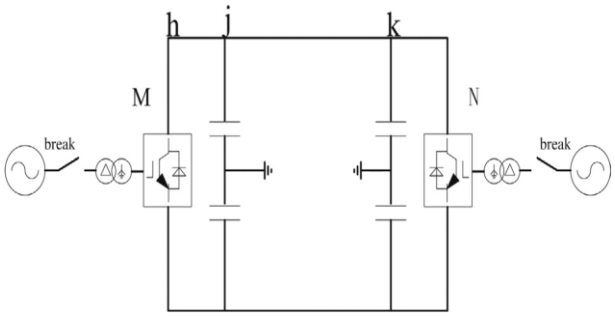

Figure 2. VSC-HVDC transmission system [36]

In the feature extraction module, HHT is used to frequency, time and energy domain feature extraction. HHT can capture the information of time and frequency. This paper utilizes the sampled current signal at single-ended DC bus to locate unipolar ground fault. It is commonly known that 0-mode and 1-mode current traveling waves have different transmission speed, due to the rapider attenuation of 0-mode current. Hence the time delay can be got by the instantaneous frequency analysis of the first Intrinsic Mode Function (IMF) component. Then the boundary spectrum of I_1 is as the characteristic frequency related to the fault distance. The 0-mode and 1-mode of current can be calculated as Eq. (9) [37, 38].

$$\begin{pmatrix} I_0 \\ I_1 \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} I_p \\ I_n \end{pmatrix} \tag{9}$$

where I_0 and I_1 are 0-mode and 1-mode current, respectively. I_p and I_n are the positive pole and negative pole current, respectively.

Except time difference between I_0 and I_1, and characteristic frequency of I_1, the features used for confirming the fault distances are also consisted of the energy attenuation coefficient of I_1 and I_0 and the high-frequency energy of I_0 and I_1. The input-output of ANFIS in the proposed method is shown by Figure 3.

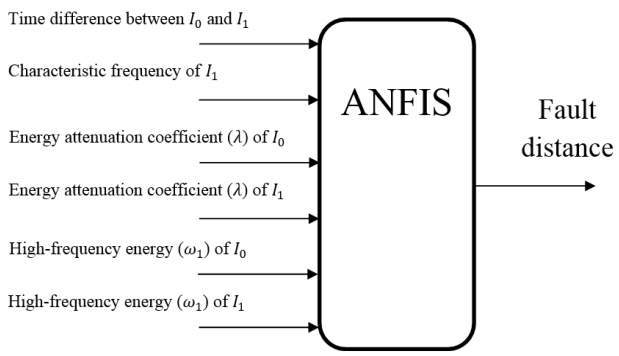

Figure 3. The input-output of ANFIS in the proposed method

Issue of the learning algorithm and its speed is very important for the ANFIS model. ANFIS is trained by using the existing input-output data pairs for the solution of available problems. Thus, IF-THEN rules in ANFIS are obtained. In [21] a new learning algorithm based on aABC is proposed for ANFIS training. The excellent performance of this method is proved by several numerical experiment. Therefore, in this paper we propose the application of this new learning algorithm to train the ANFIS in the field of fault location in VSC-HVDC systems.

In training of ANFIS, antecedent and conclusion parameters found in layer 1 and 4 are optimized. In this study, the mentioned parameters are optimized by using aABC algorithm. The parameters which belong to ANFIS structure used in training are seen in Figure 1. Number of parameters found in structure of ANFIS and to be used in training is equal to the total of number of antecedent and conclusion parameters. In aABC algorithm, the position of a food source represents a possible solution for the addressed problem. Therefore, a set of antecedent and conclusion parameters of ANFIS correspond to a food source in aABC algorithm. Thus, aABC algorithm operates for finding the best food source around the hive or the best antecedent and conclusion parameter set in the search space.

In the proposed method we used mean square error (MSE) as fitness function. The mathematical representation of MSE is as Eq. (10)

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (d_i - O_i) \tag{10}$$

where O_i is output value of ith training samples, d_i is the expectation, and N is the number of samples.

4. Simulation Results

4.1. Data

In this section we evaluate the performance of the proposed recognizer. For this purpose a dual-loop PI control VSC-HVDC system as shown in Fig. 4 is modeled in computer software. The power transmission of system is 75MW and the DC voltage is 110 kV. Because the existing HVDC lines are mostly overhead lines, the simulation of this paper adopts coupled overhead lines quoted frequency dependent model with the sampling frequency of 1 MHz, and the length of line is 250 km. The capacity of capacitor nearby the DC bus is 1000 μF. The grounding resistance of training samples is 10 ohm.

In order to train ANFIS and do preferences, this paper picks up the negative pole grounded fault cases which happen on the transmission line per 5 km. Each of the faults adopts merely current signal to get the features. To eliminate the differences of multiple input samples and improve the generalization ability, the input should be normalized. All input data is normalized to let the input amplitude range distribute in the interval (0, 1).

In order to better explain the validity of the features proposed, Figures 4 to 8 reveals the relationship between the normalized feature and the fault distance. In this figures, the horizontal axis shows the fault distances in Km scale and vertical axis shows the value of feature. As shown in Figure 4, the time differences between I_0 and I_1 are roughly linear to the fault distance and characteristic frequency of I_1 fall obviously with the increase of fault distance in Figure 5.

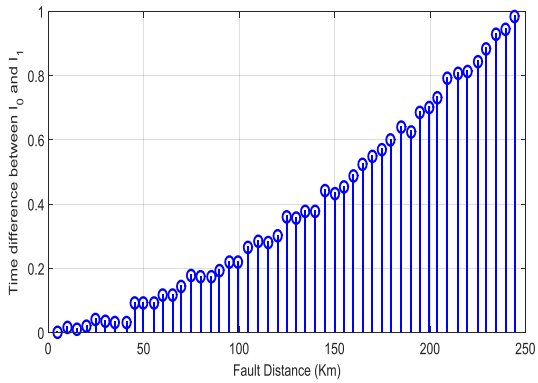

Figure 4. Normalized feature for faults with different distance, Time difference between I_0 and I_1

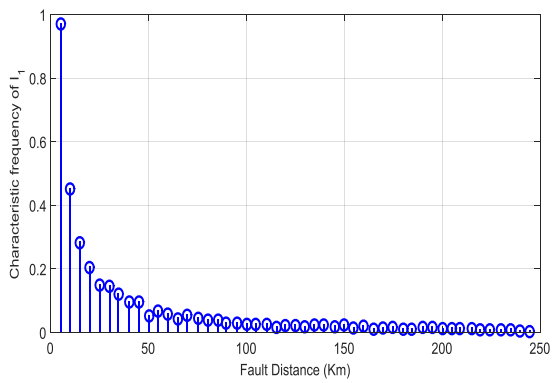

Figure 5. Normalized feature for faults with different distance, characteristic frequency of I_1

From Figures 6 to 8, it is showed that the energy attenuation coefficient λ and high-frequency energy ω_1 appear regular fluctuations with different fault distance. It can also be seen from these figures that the time differences between I_0 and I_1 was used for coarse global refinement, and characteristic frequency of I_1, the energy attenuation coefficient λ as well as high-frequency energy ω_1 were used for fine local refinement.

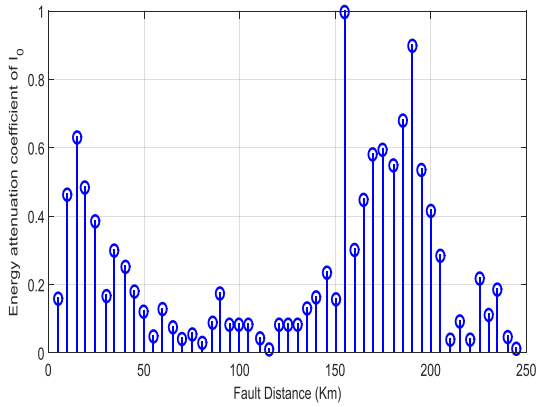

Figure 6. Normalized feature for faults with different distance, energy attenuation coefficient ($\boldsymbol{\lambda}$) of $\boldsymbol{I_0}$

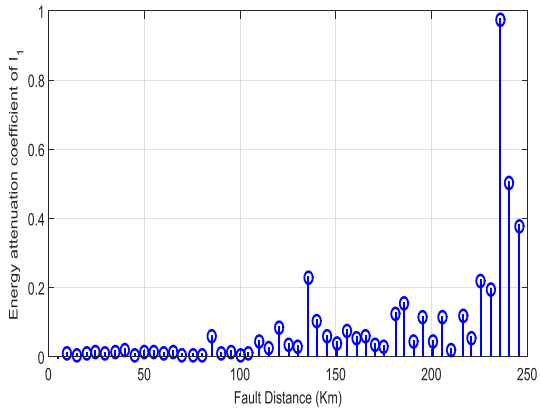

Figure 7. Normalized feature for faults with different distance, energy attenuation coefficient ($\boldsymbol{\lambda}$) of $\boldsymbol{I_1}$

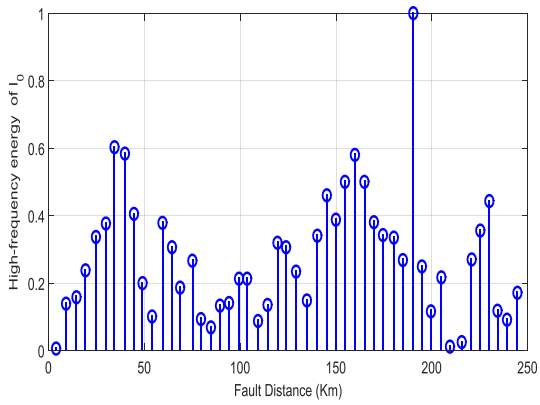

Figure 8. Normalized feature for faults with different distance, high-frequency energy ($\boldsymbol{\omega_1}$) of $\boldsymbol{I_0}$

4.2. Performance of the Proposed Method

To verify prediction accuracy of the unknown fault, this paper chooses randomly 15 unipolar ground fault cases and the results verify that the method can be used for fault location of VSCHVDC. The aABC algorithm is utilized to train the ANFIS. Input variables are modeled using Gaussian membership function. In this case, 3 membership functions are utilized for each input and 8 rules are obtained. Each Gaussian membership function has two parameters including sigma (σ) and center (C). So we have $(6 \times 3) = 18$ antecedent parameters. Also we have $(8 \times 7) = 56$ conclusion parameters. Thus, $(6 \times 3) + (8 \times 7) = 74$ unknown parameters are optimized using aABC to build an ANFIS with the highest accuracy.

The results that achieved by the proposed method, optimally learned ANFIS and selected features, are listed in **Error! Reference source not found.**1. In this table, the second column shows the fault distance, the third column shows the estimated distance using raw data (current signal) and the forth column shows estimated distance using proposed features.

Table 1. Performance of the proposed method

Fault pole	Distance (Km)	Estimated distance (km)	
		Current signal	Proposed features
Negative	27.3	27.64	27.48
Positive	42.5	43.19	42.72
Positive	56.2	55.96	56.49
Negative	79.4	80.13	79.94
Negative	91.6	90.47	91.21
Negative	110.6	110.32	110.83
Positive	123.9	124.51	124.16
Negative	146.3	145.03	146.64
Positive	163.5	164.87	164.18
Positive	170.8	171.28	170.7
Positive	190.5	190.93	190.86
Positive	210.6	210.97	210.78
Negative	226.1	226.89	226.41
Positive	242.8	242.46	242.96
Error		MSE=0.5128	MSE=0.265

The value of MSE for two type of inputs are 0.5128 and 0.1067 respectively. In Figure 9, the accuracy of optimized ANFIS with two type of inputs has been compared. It can be seen that ANFIS with optimal structure and proposed features has much better accuracy.

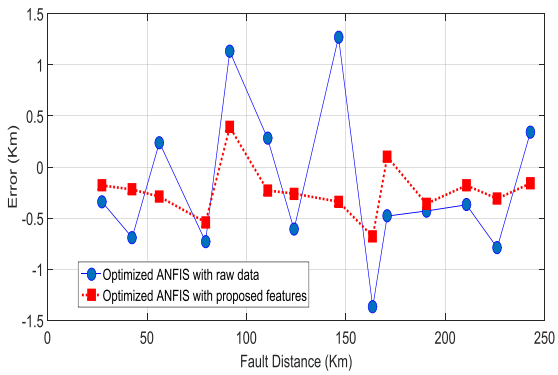

Figure 9. Performance of ANFIS with optimal structure proposed features

4.3. Comparison with Different Machine Learning Methods

The performance of the proposed method has been compared with other machine learning method for investigating the capability of the proposed method, as indicated in Table 2. In this respect, multilayer perceptron

neural network (MLPNN) with different training algorithm such as Back propagation (BP), Ladenburg -Marquardt (LM), and Resilient propagation (RP) learning algorithm, probabilistic neural networks (PNN) and support vector machine (SVM) are considered. In this experiment, the six proposed features using HHT are used as input of different estimators. It can be seen that the proposed estimator (aABC-ANFIS) has better performance than other methods.

Table 2. Comparison the performance of proposed method with other machine learning methods.

Estimator	MSE
MLP (BP)	1.3286
MLP (LM)	0.3672
MLP (RP)	0.3811
PNN	0.4679
SVM	0.3892
aABC-ANFIS	0.265

4.4. Comparison and Discussion

Considering the importance of the fault location in HVDC systems, in the recent years extensive studies have been conducted to fault location successfully. Direct comparison with other works is difficult for HVDC fault location problem. A different setup of faults (for example, the number of training and testing samples and the number of samples) will lead to different performance. Besides, there are many different kinds of benchmarking system used for system quality. This causes difficulties for direct numerical comparison. Table 3 compares some different methods in case of: MSE and the used inputs. The third column in this table, shows the input type. The literature review has shown that the input type has high effect on estimation accuracy and estimator performance.

Table 3. Comparison of proposed method with other methods

Ref. no	Year	Input type	MSE
[39]	2014	Natural frequency of current	0.37
[5]	2017	Frequency spectrum	0.31
This work	-	Time-frequency domain features extracted using HHT	0.265

In [39] researchers have presented a novel method for locating fault on VSC-HVDC transmission line using one terminal current data. The proposed method is developed based on the natural frequency of distributed parameter line model. Also in [5] researchers have proposed a one-end gap-based fault location method for VSC-HVDC transmission line using the fault current signal. In this method, using the post-fault current time series, the frequency spectrum is generated for measuring the gaps between the contiguous peak frequencies. As it can be seen in the results, the proposed method has better performance that other similar methods.

5. Conclusion

HVDC connections enable integration of wind power plants located very far from shore. In this study a fast intelligent and accurate method was proposed for fault location in VSC-HVDC systems. In the proposed method, frequency and time domain features have extracted so that the location would be better and the volume of computation would be reduced. A new learning algorithm based on the aABC algorithm was used to train the ANFIS. Several experiments performed to evaluate the performance of the proposed method.

In first experiment, the performance of optimized ANFIS investigated using two kind of inputs: raw data and proposed features. The value of MSE for two type of inputs were 0.5128 and 0.1067 respectively. Observed that ANFIS with optimal structure and proposed features has much better accuracy.

In the second, the performance of the proposed method compared with other machine learning method for investigating the capability of the proposed method. Observed that the proposed estimator (aABC-ANFIS) has better performance than other methods. In the third experiment, the performance of proposed method compared with other similar methods introduced in the literature. The obtained results showed that the proposed method had better performance rather than other methods.

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