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A Hybrid Method for Fault Location in HVDC-Connected Wind Power Plants Using Optimized RBF Neural Network and Efficient Features

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Keywords

Offshore wind power plants,
VSC-HVDC,
Fault location,
RBFNN,
Bee's algorithm.

Abstract

High voltage direct current (HVDC) transmission system is going to become the most economical and efficient way of power delivery for large and remote offshore wind power plants. Designing an accurate and fast fault location method in HVDC-connected wind power plants is necessary to maintain uninterrupted power delivery and protect sensitive devices of these systems. This paper proposes a hybrid method for fault location on voltage source converter HVDC (VSC-HVDC) transmission line which connects the wind power plant to the main AC grids using one terminal current data. The proposed method includes three main modules: the feature extraction module, the estimator module and learning algorithm module. In the feature extraction module, frequency feature are extracted using wavelet transform. In the estimator module, radial basis function neural network (RBFNN) is used. In RBFNN, learning algorithm has a high impact on the network performance. Therefore, a new learning algorithm based on the bee's algorithm (BA) has been used in the learning module. The proposed method is tested on 250 km VSC-HVDC transmission line. The obtained results have shown that combination of proposed feurears and Bee-RBF has accuracy in fault location in HVDC systems.

1. Introduction

Renewable energy resources, such as wind, solar and geothermal power, are clean alternatives to fossil fuels. They produce little or no pollution and they will never run out. Among the renewable energy resources, using wind energy is growing rapidly due to economic saving and safe utilization. It is predicted that 10% of the European Union's electricity will be generated from the wind energy by 2020 [1]. In addition to land-based wind power plants, offshore power plants have great potential to supply the main grid with the electrical power. In fact, the electrical power which can be received from the offshore power plants is more than the land-based wind farms because of high winds at sea [2].

From power transmission's point of view, there are two types of connections, HVDC and AC connection. Economic matters play major role in selecting the best way to transmit the electrical power from offshore substation to onshore substation. According to research studies have been published in the literatures, for large and remote wind power plants, the HVDC transmission sounds more interesting way to deliver the electrical power to the main AC grid [2- 4].

The fault location of HVDC transmission lines is an extremely tough job due to the long lines, severe weather condition and varied topography. Therefore, its of great significance to vigorously develop fault-location techniques for HVDC transmission lines. In recent years, machine learning algorithms such as support vector machine (SVM), fuzzy systems and artificial neural networks (ANNs) have been implemented for the detection and location of faults in HVDC systems. Hao and et al have used SVM for detection and location of faults in HVDC systems [5]. They have used time-frequency features of current signal as input of SVM. Simulation results have shown that SVM has acceptable performance for fault location in HVDC systems. However, the accuracy of an SVM is dependent on the choice of the kernel function and the parameters (e.g. cost parameter, slack variables and the margin of the hyper plane.) Failure to find the optimal parameters for an SVM model affects its recognition accuracy [6]. Another drawback of the SVM is its computational cost [7].

Paily et al. [8] have used fuzzy approach to faults detection and location in HVDC systems. The fuzzy systems have a strong inference engine containing fuzzy rules that can detect hidden relations which is unrecognized by the

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human expert. On the other hand the error rate of fuzzy systems is high as they suffer from the drawbacks of random initial cluster center selection and requirement of large training dataset [9]. ANNs have been widely applied to faults detection and location in HVDC systems. For example, Vasanth and et al have used multilayer Perceptron neural network (MLPNN) to fault detection in HVDC systems [10]. They have used raw current and voltage signal as input of MLPNN.

Based on the published papers about the estimating of faults location in HVDC systems, there are some facts which should be considered during the design of recognizer. One of these issues is the feature extraction. In this paper, the frequency features extracted by wavelet decomposition are used as input of estimator. Another issue is related to the choice of the estimation approach to be adopted. The developed method uses RBFNN for locating task. RBFNN is good at tasks such as pattern recognition, function approximation and nonlinear time series prediction [11- 13].

The locating of faults in HVDC systems using machine learning methods basically consists of two phases: training and testing. In the training stage, weights are calculated according to the chosen learning algorithm. The issue of the learning algorithm and its speed is very important for the RBFNN. Different methods have been used to train RBFNN. This paper proposed to use the Bee-Inspired RBFNN introduced in the study by Cruz et al. [14] as a learning algorithm.

The rest of the paper is organized as follows. Section 2 explains the needed concepts including offshore wind power plant, the feature extraction and RBFNN. Section 3 presents the proposed method. Section 4 shows some simulation results and finally section 5 concludes the paper.

2. Needed Concepts

2.1. Offshore Wind Power Plant

In order to present a robust fault detection method, it is vital to have enough knowledge about the VSC-HVDC system and its behavior under different circumstances. It is useful to investigate transient state of the system when different faults happen. The single line diagram of the simulated offshore wind power plant system is shown by Figure 1.

There are three main sections in offshore wind farms connected to main AC grids namely (1) wind generation section, (2) HVDC transmission section and (3) the main grid section. The first section contains high power wind turbines at sea. The offshore wind power plant transmits its power by the HVDC transmission system. The second section is the HVDC transmission section consisting of marine substation, long submarine HVDC cable and onshore substation. Finally, the third section is the AC main grid. Usually, there is a power transformer to adjust the voltage magnitude of the inverter for connecting to the main grid which is called converter transformer.

Faults may happen in each mentioned sections of the system. Types of faults may happen in the first and the third sections are AC faults. On the other hand, DC faults may occur in the second section. When a DC cable fault (pole to pole fault or cable ground fault) happens, DC current suddenly increases and contains two main current: anti-parallel diodes currents (i_{vsc}) and capacitor discharging current (i_c) as shown in Figure 2.

The IGBTs will be blocked rapidly and anti-parallel diodes start to feed the fault current from the AC side. Paths of the fault current when the positive cable ground fault happens are depicted in Figure 3. Noticeable point is that the first contributor of the fault current is ic because of small time constant of the DC capacitor [2].

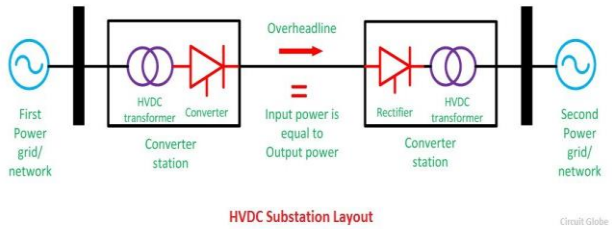

Figure 1. The single line diagram of the simulated offshore wind power plant system [2]

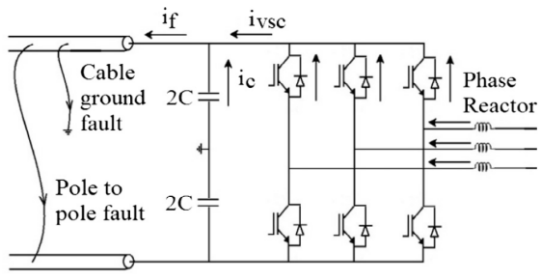

Figure 2. Contribution of different currents under cable fault condition [2]

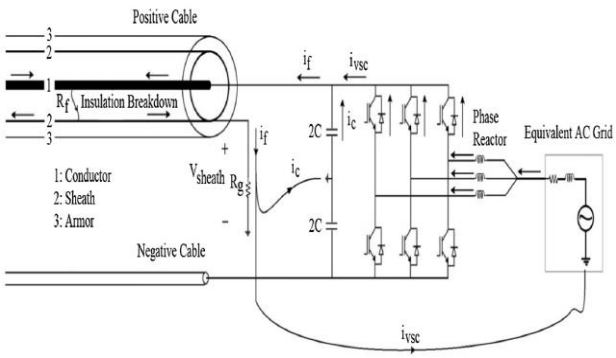

Figure 3. Current paths under positive cable ground fault condition [2]

As shown in Figure 3, XLPE HVDC cable contains the main conductor and two conductive layers: the sheath and armor separated by insulation. Under normal operating condition, no current passes through the sheath. On the contrary, under fault circumstance, the fault current passes through the cable sheath as can be seen from Figure 3. As a result, the cable sheath encounters transient over voltages. Sensors for measuring sheath voltage can be installed at each substation where the sheath connected to the ground electrode.

The DC capacitor discharging leads to very fast and severe rising of the sheath voltage. Therefore, the rise time of the sheath voltage signal as a DC fault occurs, is smaller

than the rise time of the sheath voltage signal as an AC fault happens. In other words, the signal of the sheath voltage in case of the DC faults has higher frequency spectrum than the same signal in case of the AC faults. This discrepancy can show itself in frequency content of the signal. In order to make this distinction clear, one of the best signal processing methods called Wavelet transform can be used.

2.2. Wavelet Transform

For the intelligent algorithm, it is essential that the model chooses the representative training features. Wavelet decomposition can capture the information of time and frequency. Wavelet transformation retains the time variable information in the signal. The transformation is, instead, on scale and frequency. It allows frequency analysis and statistical analysis, with time captured in the multiple levels of decomposition. However, proper choices of wavelet family, order and decomposition level are needed to retain the signal characteristics. multiresolution wavelet analysis (MRWA) provides a collection of the mathematical theory to denote a function by means of projection onto a nested sequence of approximation spaces, where the wavelet coefficients will be applied as the parameter that determines where the data distribution can be coarsened or refined. Multi-resolution analysis was developed by Mallat [15] as an efficient and practical filtering algorithm. It was created as a theoretical basis to denote signals that decompose in finer and finer detail. The first stage of decomposition will give the first level approximation which if decomposed will give the second level approximation and so on. Detail analysis is applied with a contracted, high frequency version of the mother wavelet, while approximation analysis is applied with a dilated, low frequency version of the same wavelet.

Denoting the wavelet coefficients with $h(i,j)$ and introducing the scaling function $\emptyset(t)$ as Eqs. (1) and (2)

$$\emptyset(t)=\sum_{j,k} h(j,k)\psi_{j,k}(t) \tag{1}$$

$$f(t)=\sum_n c_n(n)\emptyset_{j,n} + \sum_n d_n(n)\psi_{j,n} \tag{2}$$

The first sum in $f(t)$ is the approximation and the second one is the details loosed during it. The approximation coefficients c_n and the details coefficients d_n for each level of decomposition can be found based on the coefficients derived from the precedent level as Eqs. (3) upto (5)

$$c_{j-1}(n)=\sum_k h(k-2n)c_j(k) \tag{3}$$

$$d_{n-1}(n)=\sum_k g(k-2n)c_j(k) \tag{4}$$

$$g(n)=(-1)^n h(1-n) \tag{5}$$

As depicted by Figure 4, the original signal Y is decomposed into four level by one-dimensional wavelet.

With G being a low-pass filter and H being a high-pass filter according to Eqs. (6) upto (9)

$$G\{a_n\}=\sum_k g(n-2k)a_k \tag{6}$$

$$H\{a_n\}=\sum_k h(n-2k)a_k \tag{7}$$

$$c_{j-1}(n) = H\{c_j\} = H \times c_j \tag{8}$$

$$d_{j-1}(n) = G\{c_j\} = G \times c_j \tag{9}$$

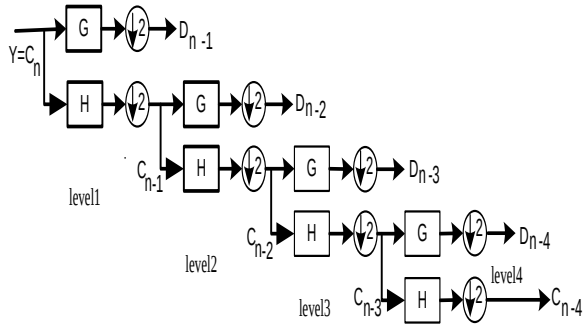

Figure 4. Multi resolution decomposition of signal Y [15]

2.3. RBFNN

RBFNN is one of the most important ANN paradigms in machine learning. It is a feed forward network with a single layer of hidden units, called radial basis functions (RBFs). RBF outputs show the maximum value at its center point and decrease its output value as the input leaves the center. Typically, the Gaussian function is used for the activation function [14].

The RBF network is constructed with three layers: input layer, hidden layer and output layer as shown by Figure 5.

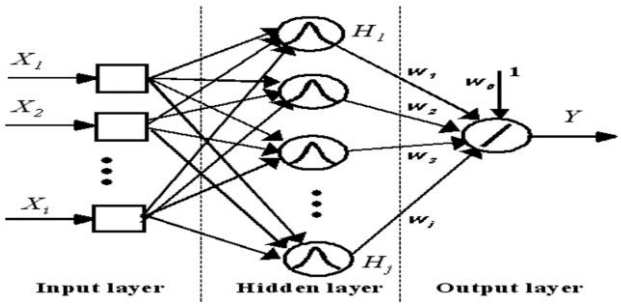

Figure 5. Structure of RBFNN [14]

In input layer, the number of neurons is the same with the number of input dimension. The input layer neuron will transmit data to the hidden layer and calculates a value of the RBFs received from the input layer. These values will be transmitted to the output layer which calculates the values of linear sum of the hidden neuron. In this study, the Gaussian function is used as RBF. Let $h_j(.)$ be the *j*th radial basis function. The output of each radial basis function is Eq. (10)

$$g_j = h(\|x - c_j\|, \sigma_j), \text{ J=1,2, . . . , m} \tag{10}$$

here, x is the input vector, $\|.\|$ is a norm, usually Euclidean, defined on the input space, c_j and σ_j are the jth center vector and the width parameter, respectively. The output of RBF network y which is the linear sum of radial basis function, is given as Eq. (11)

$$y = w_i^T g = \sum_{j=1}^{m} w_{ij} g_i\,, \qquad i = 1,2,\dots,O \tag{11}$$

where y is the output of the RBF network,$w_i = [w_{i1}, w_{i2}, \dots, w_{im}]^T$, $i = 1, 2, \dots, o$ are the network weight vectors for each output neuron i, $g = [g_1, g_2, \dots, g_m]^T$ is the

vector of basis functions and o is the number of network output units.

To construct RBF network, the number of the hidden layer neuron m must be set. Moreover, the centers c_j, the widths σ_j and the weights w_j must be estimated. In RBF typical learning, the network structure will be determined based on prior knowledge or the experiences of experts. The parameters are estimated using either the clustering or the least mean squared method.

2.4. Bee-RBF

The RBF neural network training process can be divided in two steps. The first involves the determination of the radial basis functions features to be used in the hidden layer of the network and the second one involves determining the weights of the output neurons. Different learning strategies can be used in the design of an RBF network depending on how the centers of the radial basis functions network are specified, such as fixed centers selection and self-organized selection. A RBFNN uses radial basis as its activation function and presents some main free parameters to be adjusted during training:

1) The number and location of the basis functions in the hidden layer;

2) The widths or spreads of these basis functions;

3) The weights in the output layer of the network.

The performance of the RBFNN strongly depends upon the number and positions of the basis functions composing the network hidden layer. The traditional methods to determine the centers are: randomly selection of the input vectors from the training dataset; obtaining prototypes based upon unsupervised learning algorithms, such as k-means clustering; or using the supervised learning to train the network. Using the fixed or self-organized centers in RBFNN have the main drawback of working with an arbitrary number of RBF centers whose positions and spreads are either randomly chosen or self-organized, respectively [14].

Many approaches have been proposed in the literature with the goal of overcoming these limitations. In Cruz et al. [14], a new learning algorithm, named Bee-RBF is introduced that utilizes the bee's algorithm (BA) inspired clustering algorithm to automatically obtain the number and location of radial basis function centers (prototypes) to be used in an RBFNN. Then, the spread of each RBF center found by algorithm is dynamically determined based on the distribution of the clustered input data. The goal of this method is to guarantee that each basis function is sufficiently spread so as to cover all the data points that lie within its radius. Using this approach, the most important parameter of RBFNN including RBF centers and spread of RBFs will be found automatically and optimally. Also the pseudo-inverse is used to find a regularized solution to the problem of defining the output layer weight.

In the Bee-RBF method, the clustering performed in the first layer of the RBFNN is done by the bees algorithm. In this method, each bee represents the centers of the clusters, and the number of clusters is determined by the algorithm. If the number of m clusters is determined, a spread must be determined for each cluster center. To do this, each vector in the data set is grouped to the nearest cluster center based on the Euclidean distance. After dividing the data between the clusters, the distance from the farthest data is determined from the center of the same cluster. For example, for the jth cluster, the spread amount (σ_j) is calculated by Eq. (12) as

$$\sigma_j = 1.1 \times d_{j\,max} \tag{12}$$

where $d_{j\,max}$ is the farthest distance from the center of jth cluster (in the same cluster (cluster j))

After determining the cluster centers and spread of each cluster by the bee algorithm, the output of the first layer 1 is calculated by Eq. (10). Based on the output of the first layer, the final output of the network is obtained using the Eq. (11). More details regarding this algorithm can be found in [14].

3. Proposed Method

This section belongs to describing the details of proposed method. The proposed method includes three main modules namely feature extraction module, estimator module and learning algorithm module. Figure 6 shows the main structure of the proposed method.

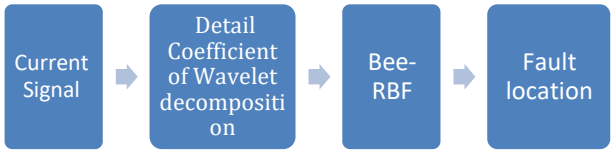

Figure 6. The main structure of the proposed method

The proposed method utilizes the sampled current signal at single-ended DC bus to locate fault. After sampling from current signal, the wavelet transform decomposes the current signal in the second module. In this module, detail coefficients of third module will be calculate and fed to Bee-RBF neural network. The fitness function of the bee's algorithm is as follow:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(d_i - O_i) \tag{13}$$

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

In this section we evaluate the performance of the proposed recognizer. Case study of an offshore wind power plant connected to 400-kV main grid by VSC-HVDC system and XLPE cables is shown in Figure 1. Nominal power of the offshore wind power plant is 400MW and the length of ±150-kV XLPE cable is 200 km. The offshore wind power plant system is simulated to generate 100 faults in different distances in DC cables. For this study, we have used 50% of data for training the classifier and the rest for testing. The computational experiments for this section were done on Intel core i7 with 16 GB RAM using ASUS computer. The computer program was performed on MATLAB (version 8.5.0.197613 [R2015a], Massachusetts, USA) environment.

4.1. Effect of RBF Numbers and Spread Value on RBFNN Performance

In this experiment, the number of RBFs is equal to the number of the training data (=50). Besides, the value of spread is tested for varying different values. The obtained results are listed in Table 1. In this table, MSE stands for MSE for all test data. It can be seen that the network with 50 RBFs and spread equals to 4.5, leads to the best performance (MSE=0.58). It can be seen that there is no linear relation between the value of spread and performance of RBFNN. Therefore the value of spread must be obtained through trial and error and based on extensive simulations. This manner of network topology selection is very time consuming. Figure 7, shows the effect of spread on RBFNN's performance.

Table 1. The performance of RBFNN

Spread	No. of RBFs	MSE
0.5	50	0.67
1	50	0.66
1.5	50	0.63
2	50	0.62
2.5	50	0.59
3	50	0.60
3.5	50	0.62
4	50	0.59
4.5	**50**	**0.58**
5	50	0.61
5.5	50	0.63
6	50	0.65
6.5	50	0.66
7	50	0.71
7.5	50	0.74
8	50	0.66
8.5	50	0.63
9	50	0.61
9.5	50	0.62
10	50	0.63

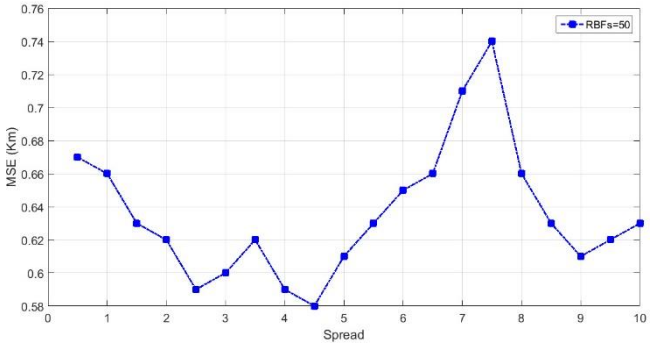

Figure 7. The effect of spread on RBFNN performance

In the next experiment, the RBFs number is selected less than training data. The obtained results have been shown by Figure 8. In this figure, the RBFNN with 25 RBFs is built and the value of spread is changed from 0.5 to 10. It can be seen that the performance of the network with 25 RBFs is better than the network with 50 RBFs. In the network with 50 RBFs, the lowest MSE was 0.58, whereas in the network with 25 RBFs and width equal to 8, the lowest MSE is 0.52. The obtained results show that the changing of RBFs number improves the RBFNN's performance significantly.

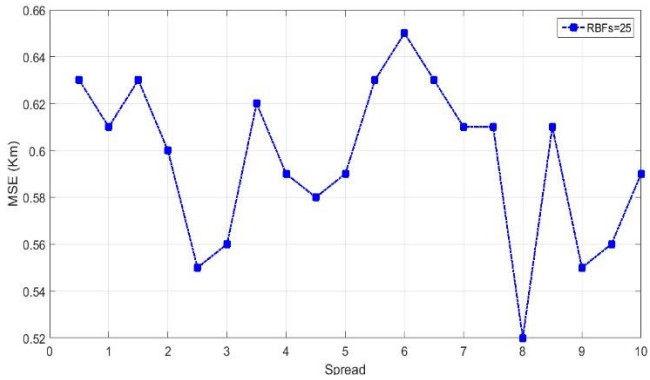

Figure 8. The effect of spread on RBFNN performance

In the previous experiments, the effect of spread on RBFNN performance was investigated and it was seen that there were no linear relation between the width (spread) value and network performance. In the new experiment, the effect of RBF numbers will be investigated. For this purpose, the number of RBFs is changed from one to 50 and the value of spread is fixed. In Figure 9, the value of spread is fixed on 5 and the number of RBFs is changed from 1 to 50 (50 is the number of the training data). It can be seen that the performance of RBFNN is highly dependent on the number of RBFs. The lowest MSE (0.49) is obtained by network with 17 RBFs and spread equal to 5. Based on this experiments it is clear that the RBFNN performance is highly dependent on RBFs number and spread value.

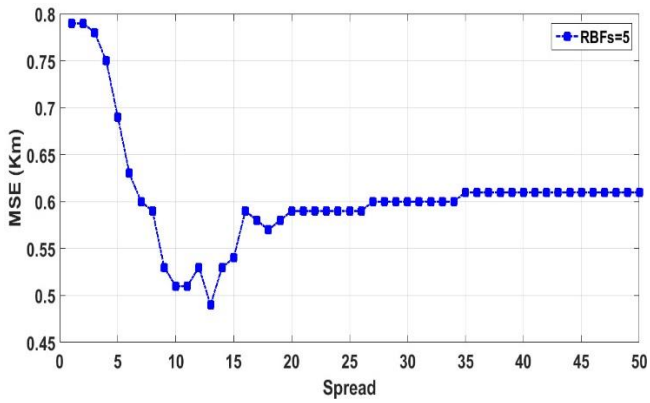

Figure 9. The effect of RBF number on network performance

4.2. Performance of the Proposed Method

The importance of optimal selection of RBF numbers and their spread is proved in the previous experiment. In this experiment, for optimal selection of RBFs center and spread of RBFs, Bee-RBF is used. The results were compared with those obtained by k-means and a random center selection mechanism. To allow a fair comparison of the methods, the value of k for k-means and the number of random centers were chosen as the same value found by the Bee-RBF approach. Table 2 presents the MSE and number of centers. The number of centers was automatically found by Bee-RBF and its rounded average value used in k-means and the random selection approach.

From Table 2, it can be seen that using Bee-RBF method, the optimal number of RBFs and optimal value of spread of RBFs are determined automatically. Using Bee-RBF provides us with decreasing the MSE to 0.24. The MSE

reduction proves the effectiveness of learning algorithm. The performance of proposed method is shown in Figure 10.

Table 2. Performance of proposed method

Clustering method	Spread	No. RBFs	MSE
Centers randomly selected	3.76	12	0.29
Centers selected by *k*-means	4.19	12	0.27
Bee-RBF	3.87	12	**0.24**

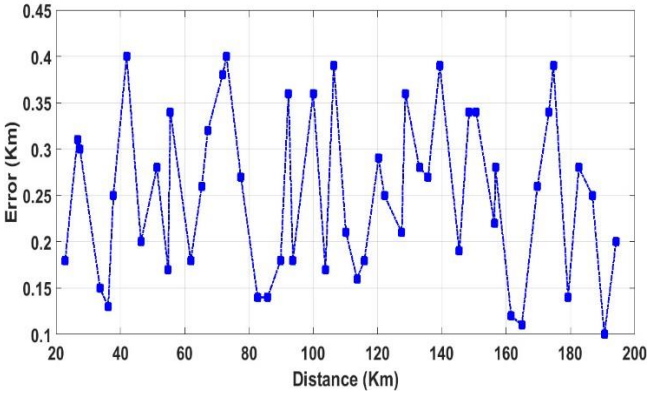

Figure 10. The performance of proposed method

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 3. In this respect, fuzzy sytem, probabilistic neural networks (PNN) and MLPNN with different training algorithm such as Back propagation (BP), Levenberg-Marquardt (LM), and Resilient propagation (RP) learning algorithm are considered. In this experiment, the frequency domain features extracted using Wavelet transform are used as input of different estimators. It can be seen that the proposed estimator (Bee-RBF) has better performance than other methods.

Table 3. Comparison the performance of proposed method with other machine learning methods

Estimator	MSE
Fuzzy	0.27
PNN	0.41
MLP (BP)	0.52
MLP (LM)	0.29
MLP (RP)	0.38
Bee-RBF	**0.24**

4.4. Comparison and Discussion

Considering the importance of the fault location in offshore wind power plants, in the recent years extensive studies have been conducted to fault location successfully. Direct comparison with other works is difficult for offshore wind power plants fault location problem. This is mainly because of the fact that there is no single unified data set available. 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 4 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 4. Comparison of proposed method with other methods

Ref. no	Year	Input type	MSE
[16]	2014	Natural frequency of current	0.37
[17]	2017	Frequency spectrum	0.31
[5]	2018	Time-frequency domain features extracted using HHT	0.28
This work	-	frequency domain features	**0.24**

Guobing et al. [16] 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. Yang and et al have proposed a one-end gap-based fault location method for VSC-HVDC transmission line using the fault current signal [17]. In this method, using the post-fault current time series, the frequency spectrum is generated for measuring the gaps between the contiguous peak frequencies. Hao et al. [5] have proposed a new method based on time-frequency domain features extracted using Hilbert-Huang Transform (HHT) for fault location in VSC-HVDC systems. In this method, the time delay, characteristic frequency, energy attenuation and high-frequency energy are used as the input of SVM to get fault distance. As it can be seen in the results, the proposed method has better performance that other similar methods. The performance of proposed method and other methods is shown in Figures 11 to 14. In this figures, horizontal axis shows the fault distance and the vertical axis shows the error rate according on KM.

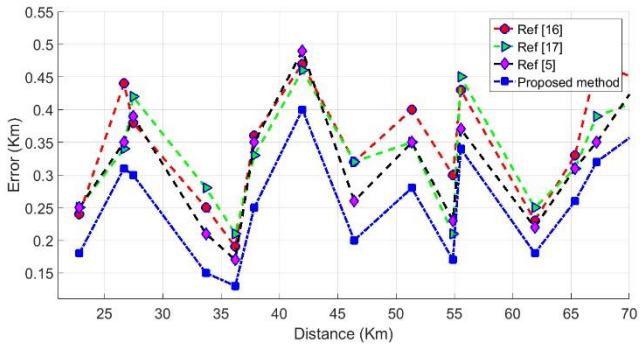

Figure 11. Comparison of proposed method with other methods for 1 Km to 70 Km

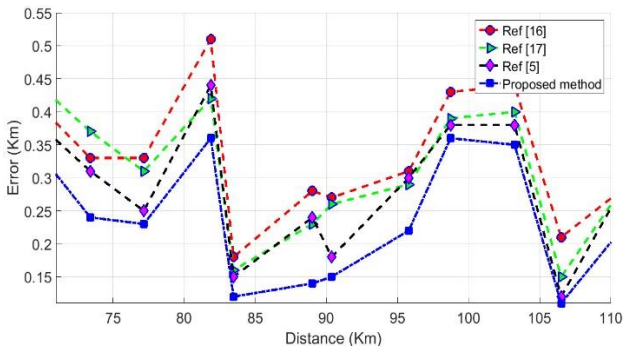

Figure 12. Comparison of proposed method with other methods for 71 Km to 110 Km

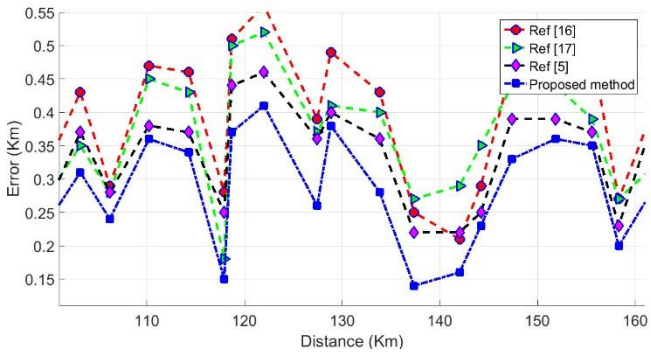

Figure 13. Comparison of proposed method with other methods for 111 Km to 161 Km

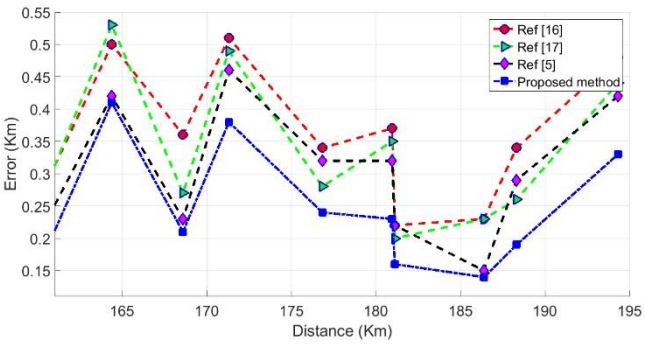

Figure 14. Comparison of proposed method with other methods for 161 Km to 200 Km

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-connected offshore wind plants. In the proposed method, frequency features have been extracted so that the location would be better and the volume of computation would be reduced. A new learning algorithm based on the bee's algorithm was used to train the RBFNN. Several experiments were performed to evaluate the performance of the proposed method.

In the first experiment, the number of RBFs was fixed and the amount of spread varied from 0.5 to 10. The simulation results showed that the performance of RBFNN is strongly dependent on the spread value. The main result of this experiment was that it showed no linear relationship between the spread and RBFNN function. Therefore, when using RBFNN, the value of this parameter must be determined by trial and error.

In next experiment, the value of spread was kept constant and the number of RBFs was changed from 1 to 50. The simulation results showed that the performance of RBFNN is highly dependent on RBFs number. Similar to the previous test, it is observed that there is no linear relationship between the RBF numbers and RBFNN performance. The experiment also showed that the network with high number of RBFs has a low generalization capability and, as a result, reduces network accuracy.

By identifying the importance of network structure and the effect of parameters on its performance, we used the Bee-RBF algorithm to find the optimal network structure. Also, frequency features were used as inputs of the network. RBFNN, with optimal structure and the use of frequency features as input, was able to correctly estimate the fault location with MSE=0.24. The proposed system has a high accuracy and therefore we recommend the proposed system for fault location in VSC-HVDC-connected offshore wind plants.

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