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Fault Detection and Classification of VSC-HVDC Transmission Lines using a Deep Intelligent Algorithm

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ABSTRACT

Considering the sensitivity of high voltage direct current transmission system protection and the difficulty in identifying external DC faults, this paper presents two methods for fault detection and classification in VSC-HVDC transmission lines. These studied methods are evaluated in terms of efficiency and accuracy. This research is focused on DC faults at different distances along the lines. DC line current and voltage are selected as input to wavelet transform, and in the next step, unique and valuable features of each signal are extracted with modern signal processing methods, and then these features are used as input data for algorithms to detection and classification faults. Deep Neural Network (DNN) and Support Vector Machine (SVM) have been investigated to detect and classify faults. In the next step, the efficiency of these algorithms was investigated and analyzed in noise conditions. The innovation of this research is replacing a new method of extracting features from the fractal dimension, which has been used to study more prominent features, and improve performance with a small number of study data and considering different conditions, and using the new feature extraction method and improving the performance of the algorithms, 96% accuracy has been achieved.

1. Introduction

Although HVDC transmission systems are not yet able to replace conventional AC transmission systems, they are widely used these days due to their efficiency. The ever-increasing expansion of power systems and the need to connect the systems of large areas and even the networks of neighboring countries to transmit energy at high power over long distances, and some technical and economic considerations increase the development of the HVDC system. since that these systems are usually built in areas with different weather conditions, they are exposed to unpredictable damage and are prone to higher failure than other power transmission systems. Therefore, the fast and reliable detection and resolution of faults have a direct impact on the safe and stable operation of the entire direct current transmission system. Due to the limitation of protection schemes to detect external faults in the direct current transmission network, to help detect faults and improve the protection of these networks, this article uses two different intelligent algorithms to identify and classify types of faults in a bipolar VSC-HVDC system. HVDC system is based on IGBT, which uses an insulated gate bipolar transistor due to fault current blocking capability. IGBT technology was already considered due to its diversity and have more advantages than thyristor-based technology. Connecting networks with different frequencies, easier control, the ability to connect renewable energies to the network, etc; are unique features of the VSC-HVDC system. In recent decades, these types of transmission systems have been recognized as an alternative to thyristor-based HVDC systems., the DC fault current increases suddenly. Therefore, it's

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impossible for conventional protection designs and devices to interrupt or deal with this current and quickly fix the fault due to limitations in breaker technology. In AC transmission systems, there is a time delay between the primary and backup protection schemes, which is unacceptable in direct current (HVDC) transmission systems due to the sudden increase in fault current. Therefore, the design and development of a special protection system for the HVDC transmission line have already been considered.

When an external fault occurs in the HVDC network, the fault current increases suddenly and intensely. Therefore, it is impossible to interrupt or deal with this flow and quickly fix the fault due to the DC line faults are mainly polarity short circuit faults. Polar faults only occur when there is significant physical damage that causes a pole-to-ground or pole-to-pole. Short-circuit faults in the DC line lead to increased DC current and overvoltage limitation.

There are two methods for measurement in HVDC transmission lines. In monopolar measurement, voltage and current values are measured in only one pole of the system. In the bipolar measurement method, it is measured from both positive and negative poles simultaneously, due to the greater use of a bipolar HVDC transmission system in transmission networks (connecting distributed generation resources to the network) in this article on a bipolar VSC-HVDC system has been investigated.

Various strategies and methods for fault detection and classification in HVDC systems can be found in the literature.

A reliable protection method can prevent misdiagnosis of faults that lead to power outages. Traditional fault detection methods in DC transmission line have mainly included voltage or current differential methods. However, the differential methods are strongly affected by the fault resistance and could not correctly identify the high resistance faults. In the following, a protection scheme adapted to traveling waves was used to detect the fault, and these forms are easily under It was affected by environmental conditions and noise. The authors [2] used the wavelet transform to analyze transmission system faults, the authors in [2] strongly suggested the importance of the wavelet transform, which has unique properties, that make it convenient for a specific application such as detection The fault is very suitable, then artificial neural network (ANN) algorithm and fuzzy logic were used to improve fault detection in a single-pole HVDC transmission network. Recently, machine learning-based methods have been widely adopted for fault diagnosis. [3] used wavelet transform method to extract features ، Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) to detect faults. [4] Ghashghaei and Akhbari have studied and investigated the CSC-HVDC transmission system and were able to detect and classify the external Faults of this system with high accuracy using machine learning algorithms, in this article the effect of noise on the signals is also considered. In the following, intelligent learning algorithms are used to identify and classify signals. [5] proposed a new deep learning method for pole-to-ground fault detection in CSC-HVDC network, this research used K-means method for fault detection, in this paper, low-level fault resistance is considered. With the development of multi-terminal networks, and the connection of renewable energy sources to the transmission network, fault detection in these networks, became essential and necessary. [21] introduced an SVM algorithm to analyze and investigate faults in multi-terminal HVDC network.

As seen, intelligent methods for fault detection and classification have been introduced, and most of this researches have been based on feature extraction using wavelet transform. In this article, first the signals are per-processed by wavelet transform and then a new method is used for feature extraction, which can be used to obtain better and more suitable features for detection and by using these features, the accuracy and Improve the reliability of algorithms.

2. The studied system and observation

The studied VSC-HVDC network is simulated in MATLAB/Simulation, this model is used to investigate various types of faults and investigate different signal processing techniques for fault analysis in the HVDC transmission line. The components of the VSC model are shown in Table 1.

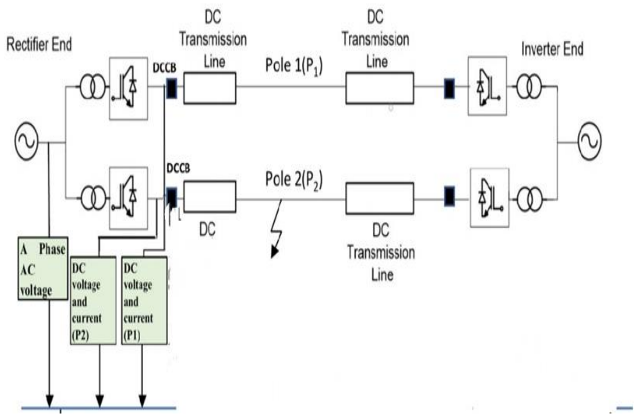

Fig 1. *VSC-HVDC schematic [26]*

Table I. Characteristics of the studied HVDC system [2]

Function	CSC – HVDC	VSC – HVDC
Converter station	Thyristor based	IGBT based
Connect to the AC network	Converter transformer	Series reactor and transformer
Filtering and reactive compensation	Filters and shunt capacitors	Only small filter
Smoothing of DC current	Smoothing reactor + DC filter	DC capacitor
Communication link between converter stations	Required	Not required

The HVDC system model is used with the specifications shown in Table I, so the maximum transmission power is 2000 MW. The frequency is 50 Hz. In this system, a 50 Hz AC system with 230 kV 2000 MVA is connected to a 50 Hz system with the same values by a DC transmission line. The length of the DC transmission line is 75 km.
VSCs are used as power transmitters at the beginning of the line and as power receivers at the end of the line, both of which have the same structure. These VSCs are used as voltage converters (inverter-rectifier) in HVDC transmission system. Therefore, it can be said that these converters are back-to-back converters. These types of networks are usually used to connect two networks with different frequencies in a long transmission network. The system studied in this research is a bipolar system, this system has two advantages over the monopolar connection:

- This system can transmit power equal to twice that of the monopole system, which is approximately equal to 3000 MW.

- In the two-pole transmission system, the poles are independent from each other, if a Fault occurs in one of the poles, the other pole can continuously transmit power and increase the reliability of the system.

Table II. Fault Simulation Parameter

Simulation Parameters	Parameters Details	Number
Types of feature	Voltage, Current	2
Numbers of Features	Vp ,Vn , Ip , In	4
Types of fault	DC positive Pole-to- ground DC negative Pole-to- ground DC Pole- to -pole	3
Fault Resistance (Ω)	1 10 50 100 150 200 250 500	٨
Measurement Point	Station 1	1
Fault location	DC LINE	1

3. Fault Analysis

External faults, which include pole-to-ground and pole-to-pole faults, have been analyzed and investigated at different intervals along the transmission line, the voltage and current waveforms of the line have been sampled from the beginning of the line to be able to Design more suitable protection plans in the future. The reasons for using both current and line voltage signals are (Due to the sudden and obvious changes in the fault current waveform, the algorithms have higher detection accuracy, and to increase the accuracy and reliability, the voltage waveform has also been used in the studies). Transient faults were also investigated in this network, which includes (switching, etc.), which we will discuss further.

3.1. DC pole-to-ground faults

In HVDC transmission systems, these types of Faults are more common than pole-to-pole faults, but they cause less damage. These faults include negative pole-to-ground fault and positive pole-to ground fault. The effect of these faults in a VSC-HVDC transmission system mainly depends on the grounding system of that system. During a fault, the DC capacitor is connected to ground at the midpoint of the DC line to prevent imbalance between positive and negative DC voltage and current. A high value of fault resistance may cause the wrong operation of the protection system. In this part, the effect of fault resistance on the performance of the proposed protection is investigated by applying faults with different resistance and in different locations of the DC transmission line.

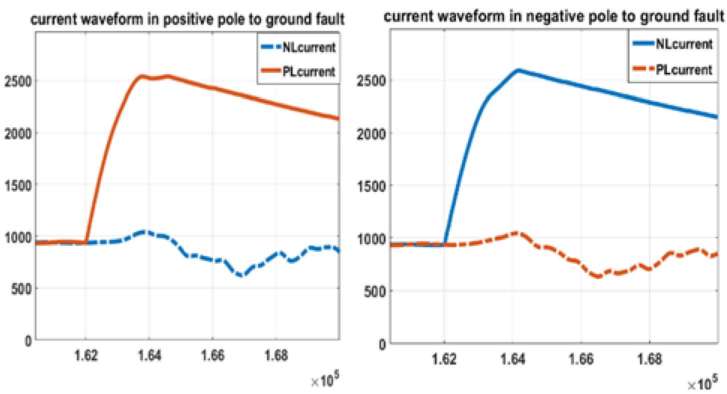

Fig 2. *DC line current waveform in pole-to-ground fault*

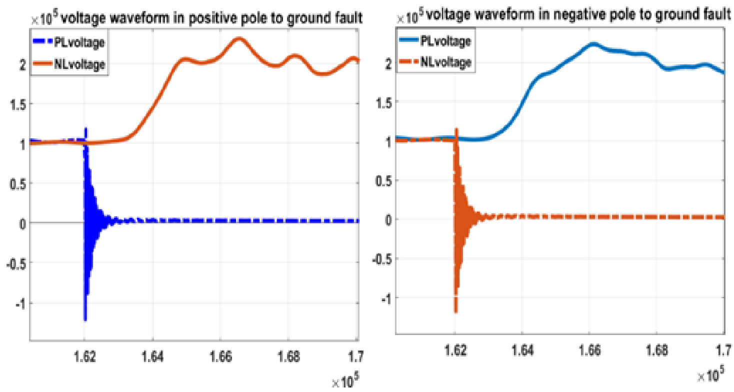

Fig 3. *DC line voltage waveform in pole-to-ground fault*

3.2. DC pole-to-pole fault

DC Pole-to-pole fault occurs due to insulation failure or direct contact between two conductors of a DC transmission line. These types of Faults are not common, but they can have serious effects on the transmission system and power outages. When the fault occurs, the communication breakers should be blocked and the DC line should be isolated from the AC circuit using circuit breakers, and finally the system should be restored after the fault is fixed.

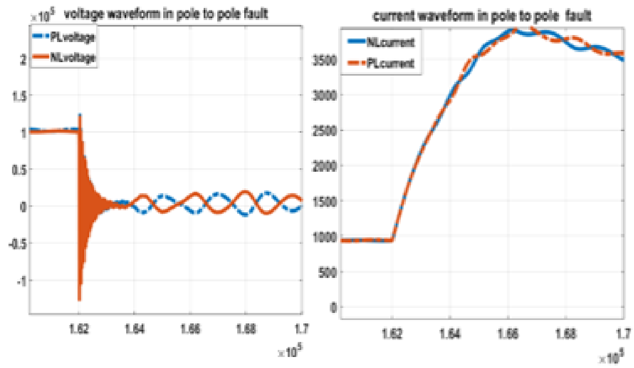

Fig 4. *DC line voltage and current waveform in pole – to-pole fault*

Table III. The Detailed specification of the test cases

Location (km)	*Rf* (Ω)	Predictions
10	10	**F-PN**
15	20	**F-PN**
17	35	**F-PN**
20	40	**F-PN**
25	90	**F-PN**
32	100	**F-NG**
36	150	**F-NG**
39	80	**F-NG**
41	64	**F-NG**
46	190	**F-NG**
49	200	**F-PG**
51	105	**F-PG**
56	300	**F-PG**
60	250	**F-PG**
70	500	**F-PG**

4. Fault Detection

When a fault occurs in an HVDC transmission system, there will be changes in the voltage and current signals. According to these changes, a criterion for starting the protective function of the protection system has been proposed. The protection scheme selects the current (Idc) and voltage (Vdc) signal as the studied data. The rate of change of current and voltage of the transmission line helps to distinguish faults from healthy and pseudo-fault states. When the DC voltage drops below the threshold value, the protection scheme considers that the system is in an abnormal (fault) state. But in pseudo-fault conditions, the DC voltage in the HVDC network undergoes transient changes. When a fault occurs along a DC line, it can be modeled as a step voltage source at the fault location, which results in some characteristics. These features can be used to distinguish Faults from pseudo-faults.

In recent decades, analysis technology has been growing and developing rapidly. Frequency analysis, time series analysis and correlation function and other methods can extract features.

A. When the system suddenly enters abnormal operation mode, the input and output signals will behave abnormally. In particular, the technical signal will behave.

B. Pre-processing: noise is removed or reduced and valuable information is increased. The fault caused by the input or measuring instrument is recovered in this process.

C. Feature extraction and Feature selection: The amount of data obtained from a waveform is too large to enter the designed model. to realize classification detection effectively, it is necessary to extract and select appropriate data and features.

D. Classification decision: samples are classified with common characteristics. The basis of the work is that, at first it is divided into a set of training samples and a set of test samples, and then decision-making and classification are done using feature extraction, and according to such a rule, the least false diagnosis follows.

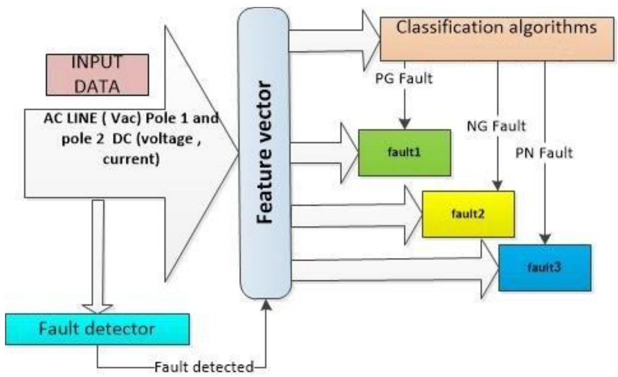

Fig 5. Proposed flow chart of fault detection and classification using learning algorithms

4.1. Fault analysis based wavelet transformer

Diagnosing and quickly fixing faults in the HVDC transmission network is still a big challenge. It is difficult to detect these Faults using pure time domain based methods or pure frequency based methods. Pure frequency-based methods are not suitable for time-transient variables, and pure time-domain-based methods are affected by noise. Wavelets are an excellent tool for digital signal processing. Digital signals can be represented using wavelet coefficients. These coefficients provide important time and frequency information that can be used to analyze signals. In addition, the signal can be processed in the wavelet domain before being converted back to the normal time-domain representation. Therefore, wavelets provide a unique framework for signal processing. the multi-resolution analysis of the signal can be evaluated in detail and approximately. The main advantage of the wavelet transform is the ability to perform local analysis, that is, to analyze a small part of a larger signal. A brief explanation of the wavelet transform is given below:

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

$$\varphi_{a,b}(t)=\frac{1}{\sqrt{a}}\varphi(\frac{t-b}{a}) \quad (1.1)$$

Each wavelet transform generally has two components: scale and transfer.

- Scale component (a) This component is equivalent to the size of the signal frequency. Obviously, the higher its value (higher frequency), the more compact the shape will be and vice versa. In fact, it will also determine the windowing length.
- The transfer component (b) will also cause the shift of this wavelet (windowing). The symbol is wavelet delay.
-

Discrete wavelet transform (DWT) is a well-known digital counterpart of CWT, known as discrete wavelet transform, as follows:

$$DWT(x,m,n)=\frac{1}{\sqrt{a_0{}^{m}}}\sum x(k)\varphi_{a.b}(\frac{n-la_0{}^{m}}{a_0{}^{m}}) \quad (2)$$

In discrete wavelet conversion, the signal from a series of high-pass filters for frequency analysis the signal is divided into two parts: the part resulting from passing the signal through the high-pass filter, which contains high-frequency information (including noise) and is called details, and the part The result of passing the signal through the low-pass filter, which includes low-frequency information and includes the identity characteristics of the signal, is called general. In this paper, the current signal is obtained in the time domain for different fault situations from both sides of VSC-HVDC lines, and then, it is analyzed through wavelet analysis. The sampling rate in this paper is considered to be 1 kHz.
Daubechies wavelet (DB4) is the mother wavelet due to its good performance in fault analysis in power systems. To better detect and check the details of the fault signal, we use the wavelet transform up to the third level to analyze the signals.
Signal preprocessing and feature extraction are applied operations to obtain the appropriate feature of a signal that can accurately represent the current state of the line. The time domain of instantaneous current and voltage signals in the DC line is obtained by simulating the power system model under different fault scenarios. In the proposed scheme, the coefficients obtained from the collected raw voltage and current signals are approximated through Discrete Wavelet Transform (DWT) processing. The appeal of DWT is that it is specific to the time and frequency domains and provides a better description because it is not just one transform, but a set of transforms, each with a different set of wavelet basis functions. Information obtained from wavelet analysis provides useful clues to locate the fault..

4.2. Feature extraction

Each signal has different characteristics that are needed to analyze and check the behavior of the signals. Feature extraction is a process in which, by operating on the data, its salient and defining features are determined. The purpose of feature extraction is to make the raw data a more usable form for subsequent statistical processing, in this research, taking into account the fractal dimensions and they of the frequency and time domains, valuable features were extracted from the processed signals. Table IIII (See appendix 1) shows those characteristics and their mathematical formulas. In all the following relationships, N is the length of the signal or the number of points that make up the signal, and X(n) is the value of the signal at the nth point. In this research, a feature vector was created from each part of the input signal after analysis in the frequency and time domains. But because in the time-frequency domain, each signal is decomposed by wavelet transform, so each signal will be increased later by combining with other feature extraction processes (such as the fractal method).
In addition to the time domain features, the features can be from the frequency domain or their combination. Usually, the output of most sensors (here the system receives the input) is in the time domain and the results are known as the raw source. In another step, the behavior of the signals obtained from the input system and its difference from other signals is measured, and done by transferring the signal to the frequency domain. Wavelet transform transfers a time signals from time domain to the frequency domain. This technique transfers a function or a set of information from the time domain to the frequency domain. This means that the Fourier transform can represent the frequency domain for a set of time information. In this step, the dominant frequencies in each signal were identified and then the frequency power of the signal was extracted using features that are used for modeling.
The combination of time and frequency domain features can also increase the richness of the features. In addition to this set of features, the fractal dimension features also contain rich information on the input signal to distinguish the corresponding class of each signal. Various algorithms have been proposed to calculate the fractal dimension, among which Higuchi's algorithm, Katz's algorithm, and simple fractal algorithm can be mentioned. Based on this, the initial fractal dimension can be calculated based on (3):

$$D=\log(L)/\log(d) \quad (3)$$

where L represents the entire length of the curve and d represents the diameter of the curve. For signals that are displayed as a set of two-dimensional points, the total length of the curve can be defined as the set of distances between adjacent points:

$$L=sum(dist(i,i+1)) \quad (4)$$

Also, the diameter of the curve can be considered as the maximum distance of a point from the starting point of the curve:

$$d = \max(dist(l,i)) \tag{5}$$

To calculate fractal dimensions, Katz's method uses an almost simple method. in this way, the sum and average Euclidean distance between consecutive points (L and a, respectively) and the maximum distance from the first point to other points are calculated (d). Then the fractal dimension of the sample (D) is calculated from (6):

$$D = \frac{\log(L/a)}{\log(d/a)} = \frac{\log(n)}{\log(n) + \log(d/L)} \tag{6}$$

Another solution is also used to calculate fractal dimensions.It is the Higuchi method, which is based on (7), the set of sub-samples *Kx* is made from sample *X*:

$$X_k^m = \{X(m+ik)\}_{i=0}^{[(N-m)/k]} \tag{7}$$

where [1, k] is $m \epsilon$ and N is the sample size. Also, *mϵ[1,kmax]* and the length of each *Xk(Lm)* is calculated according to (8):

$$L_m(k) = k^{-1} \sum_{i=1}^{(N-m)/k} \left| X(m+ik) - X(m+(i-1)k) \right| (N-1) / ([(N-m)/k]k) \tag{8}$$

In the current research, all three algorithms are used to calculate the fractal dimension. In this research, a feature vector was created from each part of the input signal after analysis in the frequency and time domains. But because in the time-frequency domain, each signal is decomposed by wavelet transform, each signal will be increased later by combining with other feature extraction methods (such as the fractal method). The extracted features were used to create a learning model and create classification and class recognition of the input signal. The advantage of this method is that by increasing the valuable features of the study, the algorithm can be trained better and the detection accuracy can be improved.

4.3. Support vector machine (SVM)

To protect the HVDC system, several protection schemes are used, specifically for fault classification. One of the methods is based on classification method (SVM), the support vector machine is a supervised learning model that is used for tasks such as classification and regression analysis. The method based on SVM is a relatively new method based on calculations,and statistical learning theory. which is always associated with high-dimensional input and can classify data with a high number of information without any restrictions. The SVM algorithm has its unique advantages. Compared to other the classication algorithms, the required sample size of SVM is relatively smaller with the same problem complexity. Since SVM uses kernel functions for multiclass classification, this algorithm can be more easily handled for high dimensional and non-linear samples. However, the accuracy of the above scheme is low for the classification of more than two classes and this algorithm is suitable for two class classifications. Overcoming this problem is the construction of multi-class SVMs through kernel functions, which we will discuss further.

4.3.1. kernel functions for multi-class SVMs

SVM algorithms use a set of mathematical functions that are defined as kernels. where it takes the input space with a low number of dimensions and transforms it into the next higher space. Simply put, the kernel turns non-separable problems into separable problems by adding more dimensions. Therefore, SVM becomes more accurate, powerful and flexible. These functions can have different types. for example, linear, non-linear, polynomial, radial and sigmoid functions. The polynomial kernel method has been used for this research.

$$k(x,y) = ([x,y] + \theta)^p \tag{9}$$

To protect the study transmission line model, two SVMs are designed. The first SVM will be responsible for fault detection, for which there are two categories, 1 (faulty mode) and 2 (healthy mode), and this algorithm can be a high-precision algorithm for fault detection, with an accuracy of 93 % follows. The second SVM will have the function of classifying the faults that we have for the three faults in the HVDC system in order: 1 (positive pole-to-ground fault) 2 (negative pole-to-ground fault) 3 (pole-to-pole fault) this algorithm is used to classify faults with 95% accuracy.

SVM confusion Matrix

	Fault	Normal	TPR/FNR
Fault	141 57.7 %	9 3.6 %	93.3 % 6.7 %
Normal	6 2.4 %	88 36 %	93.6 % 6.4 %
PPV/FDR	95.9 % 4.1 %	90.7 % 9.3 %	93.7 % 6.3%

Fig 6. *Fault detection by SVM method*

Confusion Matrix for SVM Classification

	P-G	N-G	P-N	TPR/FNR
P-G	49 32.6 %	1 0.6 %	2 1.0 %	94.2 % 5.8 %
N-G	1 0.6 %	50 33.0 %	0 0.0 %	98 % 2 %
P-N	3 2.0 %	0 0.0%	44 29.1 %	93.6 % 6.4 %
PPV/FDR	90.3 % 9.7 %	98 % 2 %	95.6 % 4.4 %	95% 5 %

Fig 7. *Fault classification by SVM method*

4.4. Fault classification by deep learning method

Despite the advantages that this algorithm has over other conventional classifications, they also have disadvantages that are tried to be minimized, including:

- It is unsuitable for big data because the training time of the algorithm is high.
- It does not work well for noisy data with overlapping classes.

The use of a new method called artificial neural networks with the possibility of deep learning instead of conventional neural networks has been widely welcomed by researchers it has recently gained many fans in the field of classification. Deep network models are neural network models developed to learn nonlinear transformations on data. Among the different types of neural networks introduced so far, the deep feedforward neural network is one of the most common of these networks. If appropriate values are chosen for its parameters such as the number of layers and neurons, the deep feedforward neural network can produce a nonlinear mapping with optimal accuracy. In other words, considering that the layers of the deep neural network are fully connected, it becomes complicated to process high-dimensional inputs or lack of access to the dataset or hardware, and the appropriate processor suffers from problems such as overloading. Fits and cannot create a desirable and generalizable model.

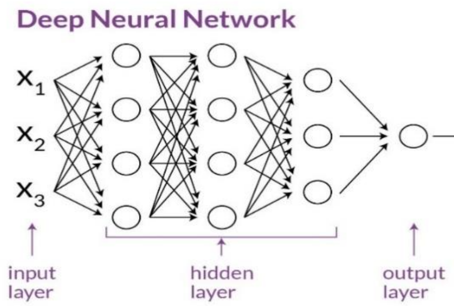

Fig 8. *The structure of a deep neural network with several hidden intermediate layers*

In this research, by using a multi-layer structure with a large number of neurons, a deep classification has been designed, the output of which can be implemented in line with the classification of all three types of input signals. According to the received features in the first layer, such as the normal neural network, after normalizing the features and also randomizing their order to help improve the classification, the outputs are fitted. This algorithm is evaluated as a deep learning algorithm for Faults classification in different conditions. The results of the simulation show that the deep learning algorithm is used to find the location of the faults faster, accurately and more reliably, and the results also show that the average detection and classification was 96%.

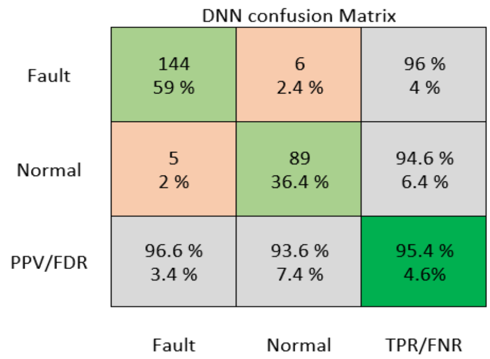

Fig 9. *Fault detection by DNN method*

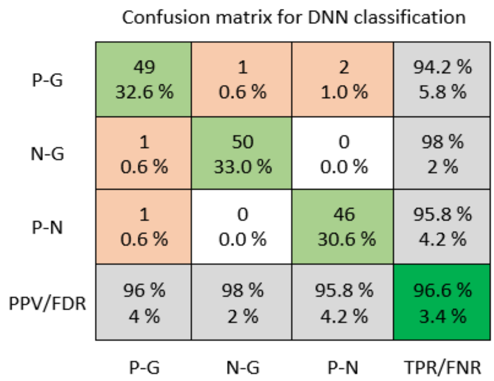

Fig 10. *Fault classification by DNN method*

The pseudo-fault state (disturbance) investigated in this article are shown in Table V. The performance of the algorithms in detecting these pseudo-faults has been investigated. These pseudo-faults are created in the AC section and create disturbances in the signals we study (Vdc-Idc). This study showed that these algorithms have an excellent performance in distinguishing the pseudo-fault state from the normal state.

Table V. Pseudo-fault specifications

Pseudo-faults	location	SVM	DNN
Sudden load increase of 3000 MW	AC line – near the inverter	N	**N**
Three phase to ground fault	AC LINE	F	**N**
Two phase to ground fault	AC LINE	N	**N**
Single phase to ground fault	AC LINE	N	**N**
phase to phase fault	AC LINE	N	**N**

4.5. *Effect of noise*

Signal to Noise Ratio is equal to the ratio of the signal power to the noise power in that signal. The signal-to-noise ratio is a measure to express the optimal performance of the signal processing system, the signal-to-noise ratio compares the signal power level with the noise power level and is usually expressed in decibels. The higher the value of the signal-to-noise ratio, the better the characteristic for a system; Because more useful information is received in the form of a signal than unwanted information or noise.

Signal-to-noise ratio (SNR) is a measure to show the amount of useful signal against disturbing signal (or noise) in electrical systems. This number is the ratio of signal power to noise power, expressed in decibels (dB). Generally, a value below 12 dB indicates a serious noise problem in the transmission lines, a matter above 20 dB is satisfactory, and a value above 30 dB is adequate.The higher this index is, the better the situation is and indicates the intensity of the valid signal.

The whole study has been done in the presence of noise again, the current and voltage signals of the VSC-HVDC transmission system have been processed with white Gaussian noise with different SNRs. All the features have been recalculated ,and the algorithms have been tested.

The results are shown in Table VI, which confirms the effectiveness of the studied algorithms.

4.6. *Highlighted of the proposed algorithms*

As mentioned in Section 1, most of the protection algorithms have been based on the concept of feature extraction using wavelet transform, and by considering the line current and voltage, they have been able to develop their proposed algorithm for fault detection and express its protection in Articles [2,3,15] used artificial neural network methods to detect faults in unipolar networks, and their performance was acceptable. [4] by combining two machine learning algorithms (SVM-KNN) was able to speed up the fault detection and classification process in the SCS-HVDC study network. Other research projects such as [21] have also used deep learning algorithms for fault detection and classification. However the main contribution of this paper and the proposed algorithm is a new insight in to intelligent feature extraction from the fractal dimension, where the combination of two or more feature extraction models through a new architecture can provide outstanding capabilities that can lead to improved detection with a small number of study data and various fault conditions. Detection and classification with a suitable feature lead to better learning and a more accurate protection model.

Our results also investigated the effect of noise on the performance of the proposed schemes. And faults with high resistance (500Ω) have been tested, while in previous articles this resistance was lower than this value. Pseudo-faults such as switching and sudden load increase, etc. have been studied and the reliability of these algorithms to distinguish these pseudo-faults from the faults has been investigated.

Table VI. Performance in the presence of noise

	SNR							
	60 dB		50 dB		40 dB		30 dB	
Algorithms	Detection Accuracy	Classification Accuracy	Detection Accuracy	Classification Accuracy	Detection Accuracy	Classification Accuracy	Detection Accuracy	Classification Accuracy
KNN	84.00%	91%	83.40%	90.80%	83.20%	89.40%	82.40%	89%
SVM	93%	95%	92.50%	95%	91.80%	94.50%	89%	92%
DNN	95%	96%	95%	95.80%	94.80%	95.50%	94%	95%

5. Conclusion

This paper presents a hybrid approach of wavelet transform and feature extraction from fractal dimension and deep neural networks. It provides detection and classification of external faults in the DC section and protects the VSC-HVDC transmission line. Detecting and classifying Faults in the conditions and characteristics of different points is the strength of these proposed algorithms. The presented method has high accuracy in all different conditions and the efficiency of this method is high for detecting and classifying faults. According to the simulation results, the presented method classifies the errors with very high accuracy, which is better than other previously proposed methods. After the classification of different methods, a comparison has been made between the methods, and the most suitable classifier has been selected according to the ratio of correct detection.

In this research, two designs for detecting and classifying faults in VSC-HVDC transmission lines are presented. The first suggestion is to use the SVM support vector machine algorithm, which based on pre-processing, feature extraction and faults detection, using individual features with high details obtained from the fractal dimension, improves its performance in detection and classification. Defects have been improved. The classification accuracy of SVM depends on the selection of training samples. Therefore, for better training of the algorithm, suitable features should be extracted from the original data. As the number of test data increases, the accuracy of this algorithm increases. The strength of this article is the increase of useful and important features by using new methods of feature extraction, which has increased the accuracy of the algorithms. The second method is to use the deep learning method, in which the use of intelligent computing for deeper learning improves performance and increases recognition accuracy. The strength of this article is the increase of useful and important features by using new methods of feature extraction, which has increased the accuracy of the algorithms. The second method is to use the deep learning method, in which the use of intelligent computing for deeper learning improves performance and increases recognition accuracy. As seen, by correctly choosing a deep network (deep feedforward network) with the appropriate number of neurons and layers, the learning of this network has been improved. In order to evaluate the sensitivity of the proposed method, the Faults was analyzed in different locations and with different parameters. The obtained results show that this algorithm, by improving the feature extraction method, has been able to achieve higher detection accuracy and high reliability with a low number of signals and by increasing important and vital features.

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7. Appendix

Table IV. characteristics and their mathematical formulas

math formula	Characteristic
$F_1 = \frac{\sum_{n=1}^{N} x(n)}{N}$	Mean
$F_2 = \sqrt{\frac{\sum_{n=1}^{N} (x(n) - F_1)^2}{N}}$	standard deviation
$F_3 = (\frac{\sum_{n=1}^{N} \sqrt{\lvert x(n)\rvert}}{N})^2$	*The root mean square of the signal value*
$F_4 = \sqrt{\frac{\sum_{n=1}^{N} (x(n))^2}{N}}$	*Root mean square*
$F_5 = \max(\lvert x(n)\rvert)$	*The value of the peak amplitude of the signal*
$F_6 = \frac{\sum_{n=1}^{N} (x(n) - F_1)^3}{N.{F_1}^3}$	*Dividing the third central moment by the cube of the mean*
$F_7 = \frac{\sum_{n=1}^{N} (x(n) - F_1)^4}{N.{F_1}^4}$	*Dividing the fourth central moment by the fourth power of the mean*
$F_8 = \frac{F_5}{F_4}$	*Crest Factor*
$F_9 = \frac{F_5}{F_3}$	*Dividing the signal peak amplitude by the root mean square of the signal value*
$F_{10} = \frac{N.F_4}{\sum_{n=1}^{N} \lvert x(n)\rvert}$	*Dividing the root mean square by the average signal value*
$F_{11} = \frac{N.F_5}{\sum_{n=1}^{N} \lvert x(n)\rvert}$	*Dividing the signal peak amplitude by the average signal value*
$F_{12} = \frac{\sum_{n=1}^{N} (x(n) - F_1)^2}{N}$	*Variance*
$F_{13} = \frac{N}{\sum_{n=1}^{N} \frac{1}{x(n)}}$	*Harmonic mean*
$F_{14} = \frac{F_2}{F_1} \times 100$	*Scattering coefficient*
$F_{15} = \frac{\sum_{n=1}^{N} \lvert x(n) - F_1\rvert}{N}$	*Average deviation from the mean*
$F_{16} = \frac{\frac{1}{N}\sum_{n=1}^{N} (x(n) - F_1)^3}{(\sqrt{\frac{1}{N}\sum_{n=1}^{N} (x(n) - F_1)^2})^3}$	*Slip*
$F_{19} = \frac{\sum_{n=1}^{N} (x(n) - F_1)^3}{N}$	*The third central moment*
$\mathrm{F}_{20} = \frac{\sum_{n=1}^{N} (x(n) - F_1)^4}{N}$	*The fourth central moment*
$\mathrm{F}_{21} = \frac{\sum_{n=1}^{N} (x(n) - F_1)^5}{N}$	*The fifth central moment*
$\mathrm{F}_{22} = \frac{\sum_{n=1}^{N} (x(n) - F_1)^6}{N}$	*The sixth central moment*
$\mathrm{F}_{23} = \frac{\mathrm{F}_{20}}{(\mathrm{F}_{12})^2}$	*FM4 parameter*