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A novel fault detection, classification and location scheme in non-homogenous MTDC transmission lines

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***Abstract*—In this paper, a protection scheme for fault detection, classification, and location in non-homogenous HVDC lines is presented based on the rate of change of voltage (ROCOV) signal attained from a single end by applying a wavelet-based signal processing tool named MODWT. The fault features extracted by MODWT are applied to a general regression neural network (GRNN) to estimate fault location. The performance of the proposed scheme is evaluated against different scenarios including fault parameter variations such as type, resistance, and location, processing parameter variations e.g. sampling frequency, noise, and ultimately topologic variations of non-homogenous transmission lines. Altogether, analyzing the results approves the efficacy of the proposed scheme in case of robustness, identification time, and noisy condition.**

Keywords-component; Non-homogenous HVDC line; MODWT; GRNN;fault detection, classification and location

I. Introduction

High-voltage direct current (HVDC) transmission systems have been developing significantly as a reliable alternative to the alternating current transmission systems. The reason for this development is HVDC systems' unrivaled advantages over the traditional AC networks, such as their lower losses [1, 2]. On the one hand, new infrastructures have been developed to exploit renewable energy sources, such as offshore wind farms. Also, there are numerous advantages in using HVDC lines instead of the traditional HVAC lines in connecting these renewable sources to the power grid, which are concerned with sustainability considerations. All of these strengths have led to the burgeoning market of this technology [3]. On the other hand, the employment of these systems faces many challenges in terms of control, protection, etc. The protection of these networks against DC lines short-circuit faults is regarded as one of the major challenges in this field. This challenge refers to the low inductance of these lines compared with AC lines, which leads these networks to suffer a rapid voltage drop and a sudden increase of the fault current in some milliseconds, at the time of a fault occurrence [4, 5].

In the past few decades and with the increase in utilizing multi-terminal HVDC networks[1], another major protection challenge in these networks has been the use of combined underground or submarine cable lines and overhead lines. These lines are generally utilized to connect offshore wind farms, as in some cases the converter's location is - for various reasons - far from the coast, which requires the use of an aerial network [6]. Currently, a limited number of combined lines, such as Basslink and Anan-Kihoku, are used in Australia and Japan, respectively [7]. Among from the main challenges, there is the lines' characteristic impedance change at the junction of the overhead lines and cables. This results in the breaking of traveling and returning waves, because the characteristic impedance and speed of travelling waves are higher in overhead lines. And consequently, a large proportion of the travelling waves emitted is weakened when entering the cable, and returns to the overhead line [8].

Few studies have been conducted on the protection of combined lines, which mostly focus on fault location. Impedance methods, artificial intelligence, traveling waves, and signal processing are among the main methods in this field.

In reference [9], identification of the faulty part of the cable or overhead line is done by modeling the error types and examining the difference in their dynamic behaviors. In reference [7], through writing KVL relations in the fault loop and measuring the voltage of the sides of the smoothing reactor, a method is provided to identify and classify errors. One of the

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shortcomings of this method is the use of the imprecise RL line model and its ignorance of stray capacitors along the cable lines, which causes a lower level of accuracy. However, the low sampling frequency is one of the strengths of this method.

In reference [8, 10], fault identification and location in combined lines are conducted through measuring the arrival time of the mobile waves' front, emitted when there is a fault in each terminal. In this protection plan, the continuous wavelet transform method is used to identify the wave front. One of the greatest weaknesses of this method is its high sampling frequency up to 2 MHz In reference [11], voltage signal decomposition into air and ground modes with a process similar to the previous references has aided the fault location in a combined line. In reference [12, 13], a method for locating the fault in combined lines is presented by measuring the difference in the value of the round trip wave, explicating the mathematical relations ruling these traveling waves, and solving the equations with the PSO algorithm. Reference [14] detects the fault in a combined line by suggesting a graph-based mathematical model for the network and using the traveling waves theory.

The differential protection method was also employed in references [15, 16] to identify and locate the fault in combined lines. In reference [15], fault detection and location were done by measuring the current and voltage at the junctions of the overhead line and submarine cable by optical sensors. However, the implementation of this method is prone to some challenges, as there is need for multiple sensors and the simultaneous sending of signals for identification in the minimum time.

In this paper a novel fault detection, classification and location scheme is proposed according to a variant of DWT with some interesting features. The location step of proposed scheme is carried out by a machine learning tool named general regression neural network. The main contributions of proposed method are as follows:

- Faster fault detection compared with other wavelet-based protection scheme
- Enable to detect classify and locate fault in both hybrid and pure DC link with single-end voltage sample
- Appropriate performance in noise condition
- Enable to detect faults up to 200Ω
- The sampling frequency of the proposed scheme is lower than other wavelet-based methods

II. Problem statement

To investigate the impact of non-homogenous lines in comparison with pure OHL or UGC lines, a comparative simulation with different DC links is carried out as shown in Fig.1. Ultimately, the fault behavior is illustrated in Fig. 2.

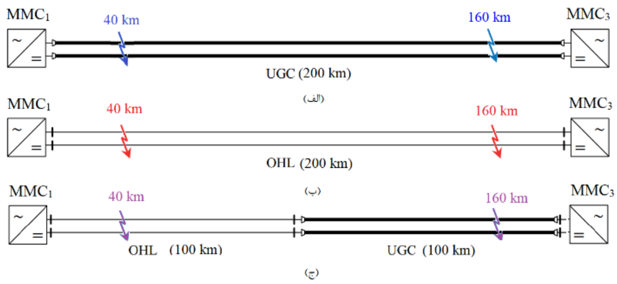


Figure 1.Fault analysis in different DC link (a)underground cable, (b) overhead line, (c)hybrid cable and overhead line

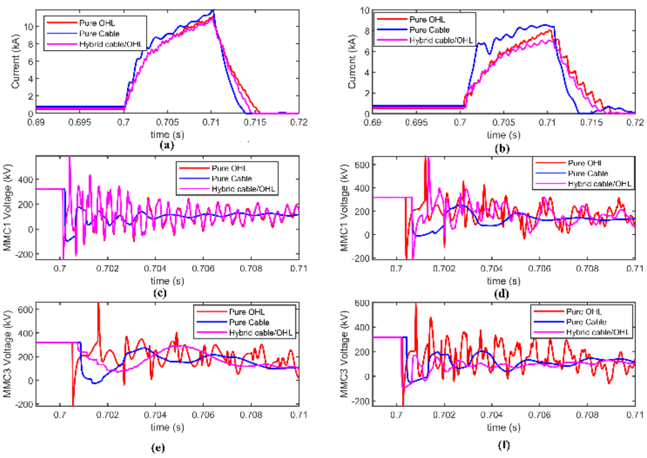


Figure 2.Fault behavior in PN fault at 40 and 160 km of line in pure OHL, pure UGC and hybrid transmission line

As seen in Fig. 2, the fault behavior in hybrid line could be different from pure lines due to the propagation velocity difference in UGC and OHL. Also the fault location and threshold setting is challenging in mixed line.

III. Proposed method

The proposed protection scheme consists of three steps illustrated in Fig. 3. These three steps which are detection, classification and location, are explained in following parts:

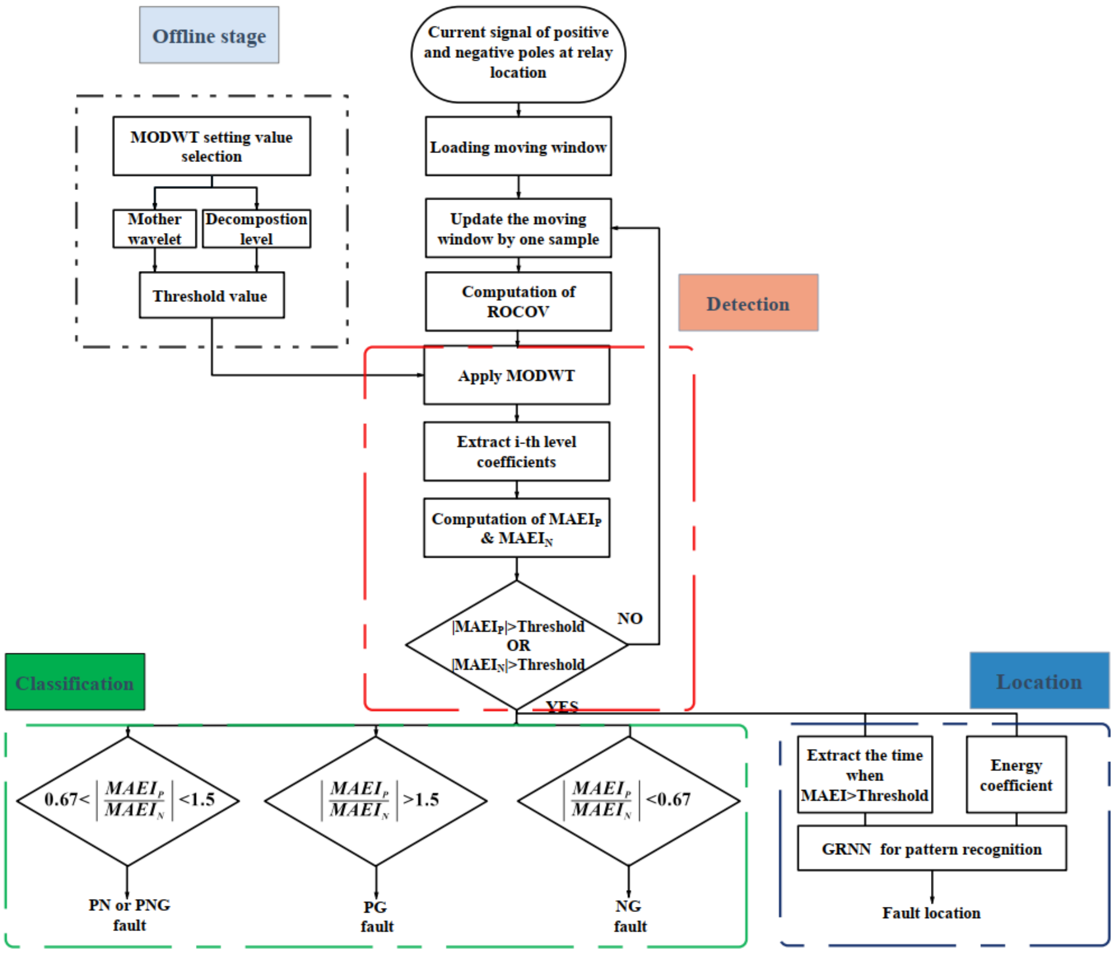


Figure 3.Flowchart of proposed protection scheme

A. Detection

The first step of all signal processing-based methods is receiving data from measurement devices. The voltage sample of both poles is selected for data analysis in this scheme due to the less sensitivity in fault loop impedance variation compared with the current signal. Also, appropriate discrimination of fault features in all protection studies is the utilization of the rate of change of voltage signal (ROCOV) as input data. This is attributed to its negligible value under normal conditions. As shown in Fig. 3, the MODWT is applied for signal decomposition. The use of MODWT aims to discern the frequency attributes of the ROCOV signal. Similar to the DWT, MODWT has the capability to sequentially break down the input signal into high- and low-frequency coefficients. Each level of decomposition corresponds to a distinct frequency band. As a result, this method enables the extraction of pertinent and essential frequency information. Also, for better discrimination, the energy of MODWT is used for fault index definition. It is worth mentioning that, the sensitivity of single wavelet energy to system fluctuations, including noise phenomenon, underscores the need for a moving average energy window. This window, determined by consecutive samples, proves beneficial in enhancing the robustness of the index. The proper decomposition level for feature extraction is according to the kurtosis index introduced in reference [17]. Furthermore, the threshold value is calculated according to the weakest internal fault (high resistance far end) and the most severe external fault in the DC and AC bus. In this paper, the selected threshold considering the reliability factor equals 12. Also, the 4th decomposition level is considered as the best frequency band for fault feature extractions. The performance of the proposed fault detection index in far-end PG and solid external PN faults is shown in Fig 4

B. Classification

Following the fault detection based on the specified threshold values, fault type classification proceeds by computing the ROCOV ratio of the positive pole to the negative pole in a data window. To compute boundary values for distinguishing various fault types, the weakest fault, occurring at the end of the transmission line with the highest fault resistance, is employed. For example, the study revealed that during a far end 200Ω PG fault, the average of ROCOVp/ROCOVn index over a data window equals 1.5. It's important to note that this index nearly equals 1 during a PN fault due to the symmetry in the transient behavior of each pole. Fig. 5 illustrates changes in the selected index for different fault types at various locations and with different resistances in the line.

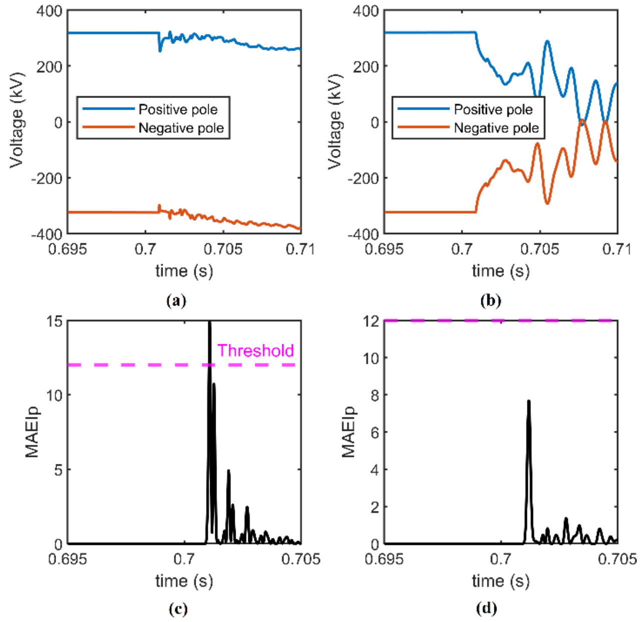


Figure 4.PG fault with 200Ω fault resistance at 200 km and external PN fault with 0.1 Ω at DC bus (a),(b)pole's voltage (c),(d)MAEIp

C. Location

After attaining some useful features extracted from single-end data, a machine learning tool is applied for estimating fault location. In this paper the generalized regression neural network is applied for the fault location step.

The generalized regression neural network (GRNN) is adept at approximating both linear and nonlinear relationships between input and output variables, utilizing a radial basis layer and a unique linear layer for real-time operation with sparse data. Unlike other learning methods, GRNN's learning process doesn't involve an iterative tuning approach, allowing for nearly instantaneous completion. With a structure comprising input, hidden, summation, division, and output layers, GRNN employs normalized Gaussian kernels in the hidden layer [19]. As a single-pass network, GRNN memorizes unique patterns during training and, without the need for back-propagation, can generalize for new inputs, demonstrating efficiency in function approximation. The architecture of GRNN is shown in Fig. 6.

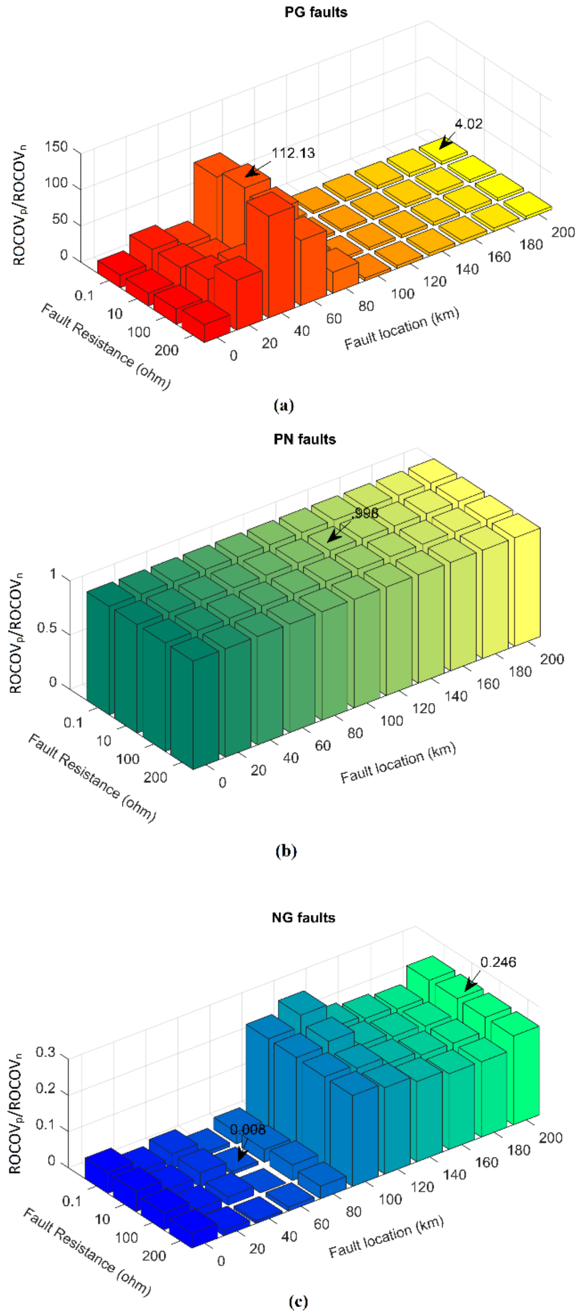


Figure 5.Classification index comparison in different fault type, resistance and location

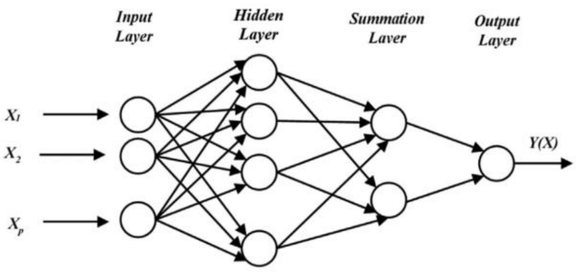


Figure 6.The architecture of GRNN

After evaluating the result of the detection and classification steps, it is concluded that the peak of MAEI both poles, arrival time, and classification index could be considered as four main features for training GRNN. For this purpose, the DC voltage of both poles is acquired at the rectifier side by using a sampling rate of 20kHz. For instance, as illustrated in Fig. 6, the architecture of the GRNN, signifies 3 neurons in the input layer, 4 neurons in the hidden layer, and 1 neuron in the output layer. It's important to emphasize that the fault location function is conducted offline, making it straightforward for implementation and application in real-world applications. A precise fault location function proves highly valuable, enabling operators to direct the maintenance team accurately, thereby reducing repair time, lowering maintenance costs, and enhancing utility reliability indices.

To generate input patterns for the ANN training process, 1212 fault cases are simulated with fault parameters variation as presented in Table. 1.

Table 1.Parameters to build training data for GRNN

Fault type	*Fault resistance(Ω)*	*Fault Location (km)*
NG PG PN	0.01 10 100 200	0, 2, 4, 6 …, 198, 200

After training process, the generalization process is started investigate the accuracy of method. The estimation accuracy is evaluated by the percentage error calculated as:

$$\%Error = \frac{Actual\ location - Estimated\ Location}{Total\ length\ of\ faulted\ line} \times 100 \quad (1)$$

In this part, 90% of data are considered for training and the remained 10% for validating the result.

IV. Results and discussions

In this section, the performance of the proposed protection scheme is investigated with various fault scenarios. Also, the impact of fault parameters, signal processing factors, and grid topology on the accuracy of fault identification is analyzed.

A. 4-Terminal MMC-HVDC grid

The simulated symmetrical monopole half-bridge MMC-HVDC grid [18] is illustrated in Fig. 7. The detailed specification of this 320kV MTDC system is presented in Table 2. Additionally, for precise modeling of the fault behavior, the frequency-dependent model for cables and overhead lines, as illustrated in Figure. 8, has been used. It's worth noting that all fault scenarios (F1 to F9) on transmission line 13 were simulated at the instant of 0.7 seconds.

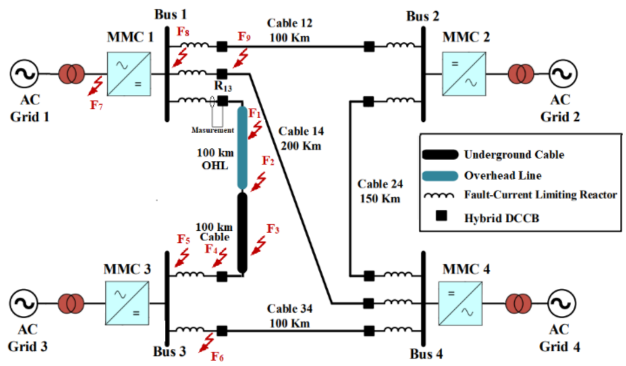
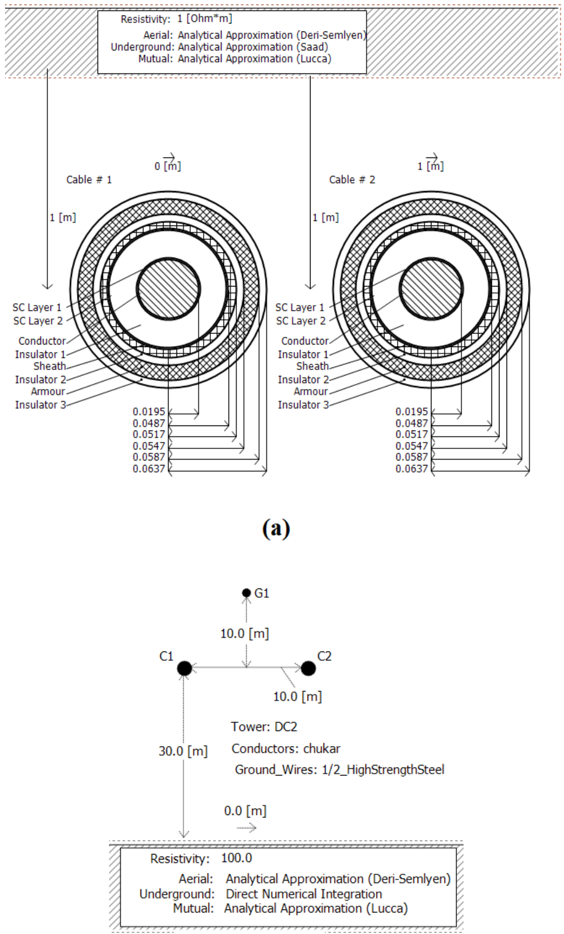


Figure 7.four terminal MTDC system



(a)

(b)

Figure 8. (a)Cable model, (b)overhead line model

Table 2.4-terminal MMC-HVDC grid specification

Parameters	Value	Value
	Conv. 1,2,3	***Conv. 4***
DC voltage	320 kV	320 kV
Nominal AC voltage (LL)	400 kV	400 kV
Nominal power	900 MVA	1200 MVA
Smoothing reactor (each pole)	150 mH	150 mH
Type of Cable	320 kv XLPE-insulated	
Model of cable	Frequency-dependent	
Sampling frequency	50 kHz	

B. *Influence of fault type, resistance and location*

In order to evaluate the impact of fault parameters on the proposed protection scheme, various fault scenarios are implemented. Fig. 9 shows the impact of fault location in both UGC and OHL. As seen in Fig. 9, when the fault distance from the relay location increases, the arrival time of fault waves will increase, too. Thus, the detection time will be more in far-end faults compared with close-in faults.

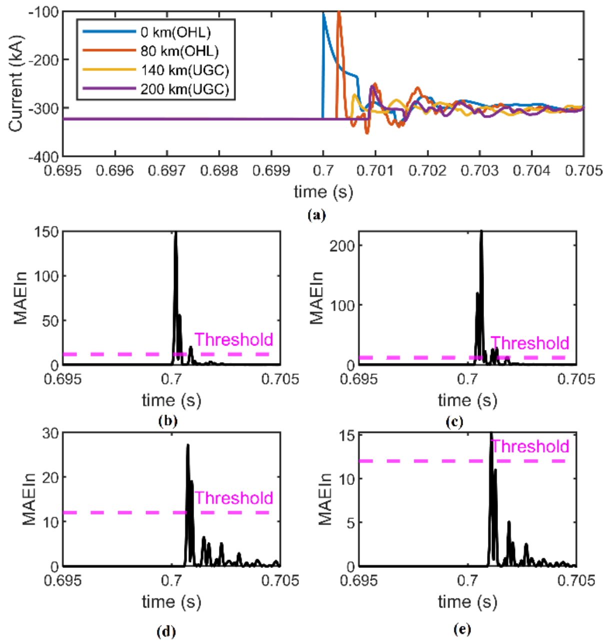


Figure 9.Impact of fault location in NG fault with 200Ω resistance,(a)voltage of negative pole, MAEIn in (b)0 km, (c)80 km, (d)140 km, and (e) 200km

Also, the influence of fault type and resistance is presented in Table 3. As seen in Table 3, the PN faults have more sever faulty behavior leading to more energy coefficient value and less fault detection time.

Table 3.Impact of fault type and resistance

Scenarios	*Fault type*	*Fault resistance(Ω)*	*Fault Location*	*$MAEI_n$*	*$ROCOV_p$/ $ROCOV_n$*
1	NG	0.1	200 km	750	0.14
2	NG	10	200 km	430	0.4
3	NG	100	200 km	43	0.51
4	NG	200	200 km	15	0.59
5	PN	0.1	200 km	990	0.95
6	PN	10	200 km	770	0.98
7	PN	100	200 km	167	0.99
8	PN	200	200 km	65	0.99

Also, the impact of fault distance on GRNN fault location is evaluated and the result shown in Fig. 10. The observed average error of estimated fault location equals 0.319% which is appropriate in a non-homogenous line due to the more complicated fault behaviors.

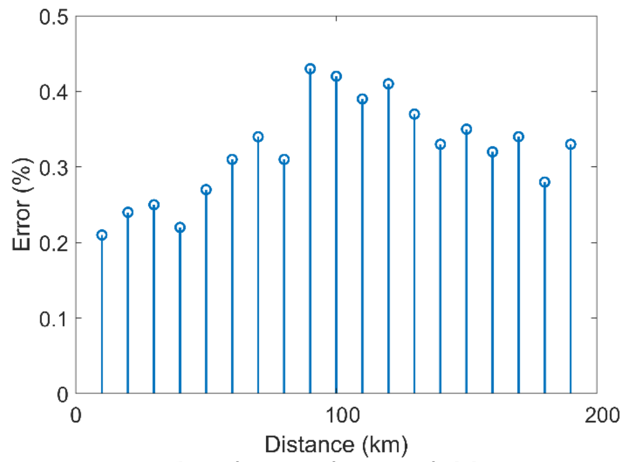


Figure 10.The performance of GRNN in fault location

C. *Influence of noise and sampling frequency*

In order to ensure the applicability of the proposed protection scheme with various measurement technologies and non-ideality, its performance is investigated in different white Gaussian noise contamination as shown in Fig. 11. It is concluded that up to 15 dB of noise the proposed scheme could thoroughly detect the fault occurrence.

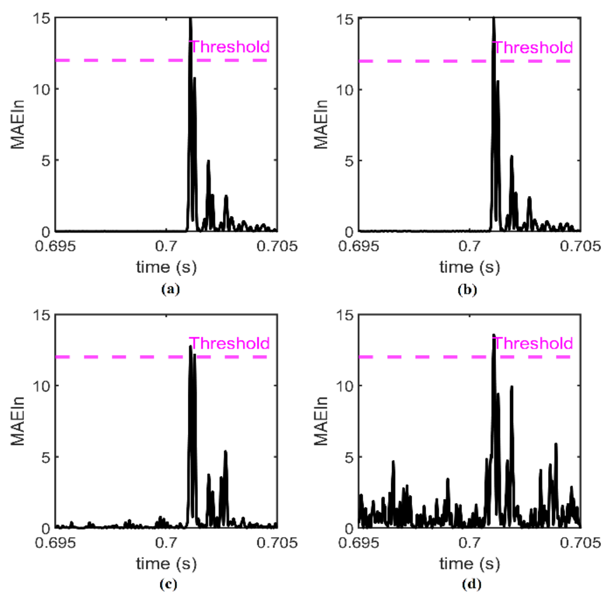


Figure 11.Impact of noise in NG fault with 200Ω resistance,(a)40dB, (b) 30dB, (c) 20dB, and (d)15dB

Also the impact of noise and sampling frequency on the accuracy of protection scheme in NG fault at the end of transmission line with 200Ω resistance is presented in Table 4.

Table 4.Impact of sampling freqeuncy

Scenarios	*Fault type*	*Fault resistance(Ω)*	*Sampling frequency*	*$MAEI_n$*	*output*
1	NG	200	100	21	Detected
2	NG	200	50	18	Detected
3	NG	200	20	16	Detected
4	NG	200	10	7	Not detected

D. Influence non-homogenous line topology

In hybrid non-homogenous line, it is necessary to investigate impact of topologic variation. Therefore, some possible topologies (shown in Fig. 12) which could influence on protection scheme performance are considered and the results of simulation presented in Table 5.

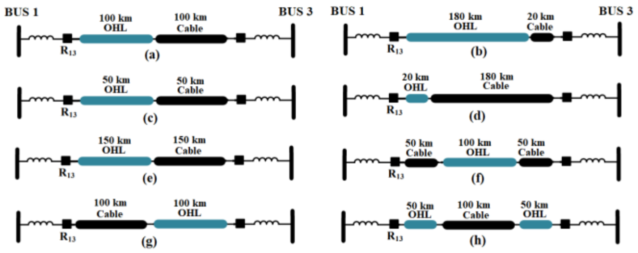


Figure 12.Topology variations of non-homogenous transmission lines

Table 5.Impact of Topology variations on protection scheme

Scenarios	*OHL length (km)*	*UGC length (km)*	*Detection accuracy (%)*	*Classification accuracy (%)*	*Location accuracy (%)*
a	100	100	100	100	98
b	180	20	100	100	98.2
c	50	50	100	100	99.03
d	20	180	100	100	94.4
e	150	150	100	100	96.7
f	100	50-50	97	100	83.2
g	100	100	100	100	98
h	50-50	100	100	100	86.4

V. Conclusion

This paper presented a single-ended protection scheme for non-homogenous HVDC line fault detection, classification, and location. The proposed scheme which integrates the MODWT and GRNN, extracts the four useful features from detection and classification steps to train GRNN for accurate fault location estimation. The main remarkable findings of the proposed schemes are as follows:

- Less detection time compared with DWT even with low sampling frequency (20 kHz)
- Fault detection capability up to 200Ω fault resistance
- Less than 0.5% error in fault location estimation using GRNN in more than 95% of simulation cases.
- Appropriate performance in noisy conditions (up to SNR=30dB)

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