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HVDC Transmission System Protection Using Neural Network

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ABSTRACT
HVDC transmission systems are electric power transmission systems based on the high-power electronics techniques. It is preferred to be used to transmit the electrical power over very lengthy distance or when transferring the power between two networks operating asynchronously or at different frequencies. Artificial neural networks (ANNs) have appeared as a robust method for solving the classification problems. Due to the ANN characteristics, it is proposed for protecting the voltage source converter-HVDC (VSC-HVDC) transmission system. The proposed ANNs are designed in this paper to detect the faults and identify their types at both the AC and DC sides of the rectifier and inverter stations. Moreover, locate the fault at HVDC transmission systems. The current signals from the transmission line two terminals are used as inputs to the proposed ANNs to guarantee accurate results. A detailed VSC- HVDC system model is created using the MATLAB software to simulate the normal and abnormal operating conditions. The fault simulation is carried out to train and test the proposed ANNs. The results prove the efficiency and accuracy of the proposed ANNs.
Keywords - ANN, HVDC, VSC-HVDC, Differential protection.

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I. INTRODUCTION

AC systems have proven their effectiveness and efficiency in the field of generation, transmission, and distribution of electrical energy. Nevertheless, in some cases, the AC systems can't be performed economically or technically perfection. High voltage direct current (HVDC) systems are electric power transmission systems based on the high-power electronics techniques. It can be used as an alternative method for transmitting the electrical power over very lengthy distance or when transferring the power between two networks operating asynchronously or at different frequencies. For these reasons, the HVDC systems are not only an economical alternative and realistic technique to AC system, but it can be considered as the only possible transmission method for these cases [1, 2].

HVDC lines should be protected to ensure both the reliability and security of the power network. So, many researches were introduced different methods to protect the HVDC systems. These methods can be classified in to two main categories: conventional and artificial intelligence protection systems. The conventional protection types include travelling wave theory based [3-21], distance protection [3, 4], boundary protection [5-11], differential protection [12-16], natural frequency based protection [17-19] pilot protection [20-21], DC voltage level [22] and directional protection [23]. While the main artificial intelligence protection types include; Artificial Neural Networks (ANN) [31-38], fuzzy logic system [39] and support vector machine (SVM) [28-29].

The shunted DC filter and smoothing reactor that connected at the two ends of the HVDC system construct the line boundary for the transient signals. This concept was used for HVDC system protection and called the boundary protection [3-7]. This boundary protection can detect fault at the HVDC very fast. But it is depended on transient so, it may be mal-operated due to the lighting strokes. The distance protection was advised for HVDC based on two models, distributed parameter, and frequency dependent parameter model [2, 3]. The model of frequency dependent parameter was applied in [2] to determine the voltage and current at the set points by using the line transformation matrix. But it may cause problems to the protection reliability. The voltage and current based distributed parameter model were calculated at the setting point [3]. By ignoring the frequency dependent nature, the determined voltage and current are affected, and this led to inaccurate values. Travelling wave protection has a high accuracy but it is unable to detect the close-up faults, this problem was solved by the boundary protection since it was able to detect close up. The lighting protection solved the problem that facing the boundary protection due to the lighting strokes. In an attempt to overcome the challenges that facing each type of these protection a combination of travelling wave protection, boundary protection and lighting protection called Hybrid protection was proposed in [4]. Hybrid protection algorithm proposed in [4] was implemented in hardware using FPGA in [5].

Wavelet based protection was proposed in [6]. It used three criterions to identify the fault in multi-terminal HVDC system. The first two criterions were the current and voltage wavelet coefficients extracted using fast dyadic wavelet transform, the third criterion was voltage derivative and magnitude. This method was depended on the initial change of the two criterions which may confuse the fault detection at the transient periods. Transient harmonic protection for HVDC system was proposed in [7]. The currents transient harmonic characteristics at both terminals was used to identify the faults. Transient voltage protection was divided into main protection and backup protection [8]. Both were depended on the installation of additional inductor at the two ends of the DC line and calculating the transient voltages ratio at the two sides o the supplemental inductor. The high frequency component of the voltage estimated at one end of the line at special frequency band was applied to detect the internal faults [9]. Protection based transient DC current was proposed in [10] where S transform was applied on the six mode currents. The polarities of the fault current component at both cable terminals were applied to detect the fault.

Conventional differential protection of HVDC systems experience problems concerning the impact of the distributed capacitance, lack of valid setting principle, and operate with delay time to trip [11]. The distributed capacitance was integrated in the Bergeron model to determine the current and voltage distributions on the line and taking a setting point on the line [12]. Furthermore, the distributed capacitive current was calculated through the linear distributed voltage and compensated in the protection criterion [13]. The two signals were used in differential protection for the HVDC systems to identify the faults through their ratio, the restraining and operating signals [14]. Both signals were based on the energy content of the current waveform at the two ends of each transmission line however this method needs high speed communication which leads to high cost and complexity of the system [15]. The transverse negative and positive poles currents at the same side of bipolar HVDC line were used to detect the faults through the ratio of difference and sum of these transient currents [16]. An improved scheme for travelling wave differential protection was introduced in [17]. The travelling wave energy ratio blocking of both fault side and non-fault side was applied to identify the faults. The directional protection was utilized to identify the faults by comparing the polarities of the transient energy in the HVDC [18]. It was based on the direction of the transient power of the travelling waves at the two terminals of the line to identify faults.

Multiple signal classification (MUSIC) method was applied on the fault current travelling wave at inverter and rectifier sides [19]. So the principal natural frequency was extracted and difference between principal frequency components at inverter and rectifier sides was used to classify the type of faults. While the MUSIC method was applied on the current travelling wave of one side to extract the dominant natural frequency and the relation between the fault distance and natural frequency [20]. This was applied to identify the fault type and discriminate between end line fault and external fault. A method of fault location was introduced in [21] which based on the natural frequency of currents. The current component and the change of the current direction monitored by directional element at both terminal of the HVDC line was proposed in [11, 22]. But the high fault resistance affects the sudden change in currents which make detection of faults very difficult. The same voltage waveform in the existing pattern in the database was used determine the fault location [23]. This method was utilized as the primary protection for the fault detection in single phase, however multi-phase faults or large fault resistance may cause problems [24].

The Pearson coefficient of correlation was applied to measure the resemblance between the current at DC link capacitor branch and at the cable end to identify the faults [25]. A fault detection based on transient voltage of cable sheath was presented in [26]. The wavelet transform in this method was applied on the sheath voltage to identify the fault. It was able to discriminate between DC cable faults and DC capacitor unbalancing. The first access times of the fault travelling waves at various travelling wave identifiers was utilized to locate the faults in the HVDC system [27]. It used a straightforward technique and an evaluation index to identify the fault sections and the faulted lines then travelling time equations were solved by least error square method to determine the fault location [27]. But fast communication between all detectors and high sampling frequency are required in this method. The installation of the predetermined value of shunt capacitor to all busbars connecting line section combined with the stray capacitance of busbars was used in [15] to identify the fault. But additional protection devices are required for protecting the shunt capacitor from faults which could cause disconnection of lines.

Artificial intelligence techniques were applied to protect the HVDC lines especially the artificial neural networks (ANNs) [30-36], support vector machine (SVM) [28, 29], and fuzzy logic [37]. SVM classifier combined with travelling wave was proposed to identify the locations of faults in the HVDC systems [28]. While the support vector regression (SVR) was applied to calculate the distance of faults based on the extracted fault features [29]. The Back Propagation Neural Network (BPNN) was applied to protect the HVDC systems [30-32]. The DC and AC side faults of the HVDC system was identified in [30], Moreover, in [31] the faults were detected and classified depending on high sampling rate. A preprocessing step in which fast Fourier transform was applied on a specific data window of the current signal was presented in [32] to identify and classify the fault types. Furthermore, the Feed forward neural network (FFNN) with preprocessing step was applied in [24, 33] for different input and output variables. The Probabilistic Neural Network (PNN) optimized by particle swarm theory was presented in [34]. The adaptive linear neuron neural network was applied in [35]. Bayesian regularization ANN and wavelet transform was applied on both terminals current signals to identify fault location for pole-to-pole faults [36]. Fuzzy logic combined with the travelling wave was proposed in [37] to identify the location of faults in HVDC systems. based on wavelet coefficients of current signals of both negative and positive pole, the fuzzy logic voter determined the faulty pole consequently the travelling wave was going to identify the fault location.

II. HVDC TRANSMISSION SYSTEM MODELLING

The voltage source converters that used with the HVDC systems are Modular Multilevel Converters (MMC), three (3L-VSC) or two Level Voltage Source Converters (2L-VSC). The MMC is classified into Clamped Double Sub-Module based MMC, Full-Bridge MMC (FBMMC), and Half-Bridge MMC(HBMMC). The first and second types of MMC are used in this paper, as they do not require a DC Circuit Breakers (DCCB) due to the capability to pull out the current in faults in the DC side. The HBMMC, 3L-VSC, and 2L-VSC have similar response to the faults in the DC side and need DCCB to clear the currents of the DC faults. Thus, this paper selects these converters, which have identical behavior for DC side faults. In this study, the HVDC with two terminals is modeled. A VSC-HVDC line is applied to transfer electrical energy from a 2000MVA, 230kV, 50 Hz to other AC system with the same data. The configuration of the considered system is illustrated in Fig. 1. As illustrated in this figure, the HVDC system is operated at rated voltage of ±100 kV. The nominal power of AC grid is 2000 MVA. The nominal power flow is considered from AC system (1) to (2). The overhead HVDC line has 75km length. It has line parameters L, R and C of 159 μH/km, 0.0139 Ω/km and 231 nF/km, respectively.

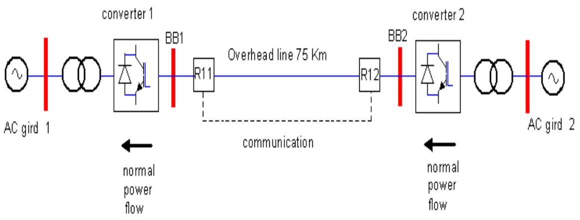

Fig. 1 Two-terminal bipolar HVDC model

A relay is installed at the two ends of overhead HVDC line. The sampling time is taken as 10μs that corresponding to frequency of 100 kHz. The HVDC is modelled and simulated using the MATLAB/Simulink. The 3L-VSC is installed at the whole system with switching frequency of 1kHz [14]. A 1mF of DC-link capacitor is connected to each converter. Converter station (1) controls both the reactive and active power while converter station (2) controls both the reactive power and DC voltage. The proposed protection system is proposed to perform various protection functions using the ANNs as follows:

- Fault detection,
- Fault zone identification,
- Faulty pole classification,
- Fault location in DC line,
- Fault identification in rectifier substation,
- Fault identification in inverter substation.

III. ARTIFICIAL NEURAL NETWORK

The ANN is defined as one of the artificial intelligent methods which are widely used in modelling and pattern classification problems. The ANN consists of at least three layers; input, hidden and output layers. The complexity of the classification problem controls the number of hidden layers. It a highly connected group of neurons or preprocessors which resembles the human brain. They are connected with interconnects analogous to the biological synapse. Specifications of the connections' weights to implement the required operation should be represented as the network's software. The output and input layers have several neurons depends on the number of outputs and inputs of the problem. While the training patterns are used to calculate the hidden layers' neurons. So, the data patterns of input-output sets are utilized to train, validate, and test the ANNs [38].

The performance and accuracy of the ANN is affected by the hidden layers and the number of neurons; therefore, it must be calculated. The training algorithms are used to minimize the errors between the network outputs and the targets. Therefore, it can model the nonlinear relations between the inputs and outputs variables without require complex equations. However, the ANNs needed large training data patterns to train and test [39-40].

IV. PROPOSED DIFFERENTIAL PROTECTION ALGORITHM

The proposed algorithm for the protection of the VSC-HVDC system is built on combined wavelet and ANN. The wavelet decomposes the current signals at each end of the HVDC line into a low and high frequency component which called approximate coefficient and details coefficient respectively. Details coefficient of the DWT is utilized in fault detection. After detecting the fault, a decision of fault type of a HVDC line is executed by the ANN.

4.1 ANN inputs

The DC current signals are acquired by a sampling rate of 4kHz at both substations and four data windows (I_{p12}, I_{p21}, I_{n12} and I_{n21}) with 20 samples data are applied as inputs to the proposed ANN. Those signals form the input vector to ANN. The input vector can be presented mathematically as follow:

$$Input\ Vector_{(k)} = [I_{p12(k)} \ldots I_{p12(k-M+1)}\ I_{p21(k)} \ldots I_{p21(k-M+1)}\ I_{n12(k)} \ldots I_{n12\,(k-M+1)}\ I_{n21\,(k)} \ldots I_{n21(k-M+1)}]^T \quad (1)$$

where I_{p12} and I_{p21} are the mean current value of positive pole measured at the inverter and rectifier sides. I_{n12} and I_{n21} are the mean current value of negative pole measured at the inverter and rectifier sides. M is the size of data window and k is the latest sample.

4.2 ANN output:

ANN fault detector: ANN output depends on the input vector. For a pre-fault conditions, the output of the ANN is equal to 0 while for post-fault conditions, the output of the ANN is equal to one.

ANN fault classifier: The fault classifier is designed to obtain the fault type in the HVDC systems. The fault classifier is activated after the ANN fault detector identify the fault. The proposed ANN fault classifier has five outputs to detect the faulty phase as: negative pole fault, positive pole fault, ground fault, rectifier side fault and inverter side fault.

4.3 ANN construction:

The proposed ANN in Fig. 2a detects the faults to identify if the input vectors belong to pre-fault conditions or post-fault conditions. The ANN used is a multi-layer feedforward neural networks (MFFNN) architecture with activation function of hyperbolic tangent which used in hidden layers. This function is appropriate for patterns classifications [2], whilst in the output layer a linear activation function is used. A moving window of length 5ms is used to catch the average value of each of the dc current signals by using 4kHz sample rate.

The input layer of the proposed fault detection ANN has 80 neurons of the mean current's values captured from both DC line terminals from both positive and negative poles. There are two hidden layers; the first one consists of 26 neurons and the second one consists of 16 neurons as illustrated in Fig. 2a. The output neuron relevant to fault detection ANN is trained using back-propagation algorithm, to vary the output from zero to one to identify the detection of fault.

Fault classification ANN has the same inputs as the fault detector. While the first and second hidden layers have 25 and 18 neurons respectively, as illustrated in Fig. 2b. The output neuron relevant to fault classification ANN is trained using back-propagation algorithm, to vary the outputs from zero to one to identify the type of the faults.

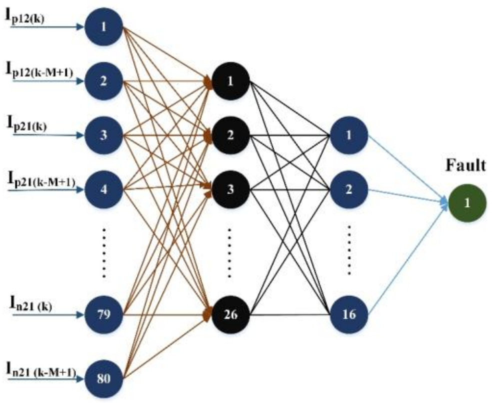

Fig.2a ANN considered for fault detection.

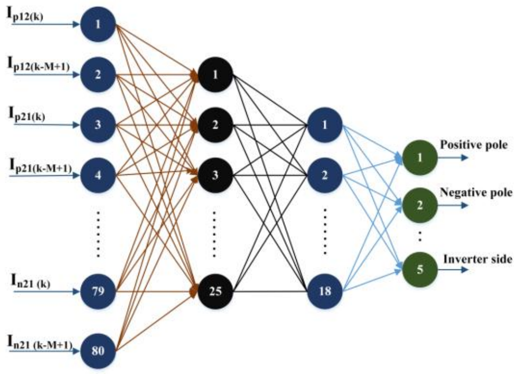

Fig.2b ANN considered for fault Classification

4.4 Training process

To train the proposed ANN a full range of normal and faulty operational conditions are taken into consideration. The pre-fault training patterns are obtained for a duration of 10ms with 5ms data window. While the training patterns of the normal operation is recorded for 20ms with 5ms data window. The training patterns are established from 66 cases based on numerous normal and faulty operating conditions of HVDC system. Each case of operating condition consists of input vectors of 22 pre-fault and 63 post-fault which result in 5412 input vectors. The input vectors of the pre- and post-fault do not get together for the training patterns. Thus, the training patterns are applied for training the proposed ANN fault detector to result in an output equal zero for input related to the normal conditions and equal 1 for input vector related to the post-fault conditions. The training patterns are obtained by simulating the HVDC system according to different parameters illustrated in Table 1. Therefore, all possible combinations do not present in the training set except a sample of the 66 training cases are chosen to represent the problem boundaries. The proposed ANN is implemented, trained, and tested using MATLAB software. The main training and testing parameters are selected as shown in Table 2.

Table 1 Proposed ANN data set patterns

Parameter	Values
Resistance of fault	0.5Ω, 10Ω, 15Ω and 20Ω
Location of fault in dc	0, 10, 20, …. and 100%
Types of AC faults	three-phase, double-phase, and single-phase
Power across the line	0.7pu, 0.8pu, 0.9pu and1pu
Magnitude of voltage at bus 1 of the AC system.	0.9pu, 0.95pu, 1pu and 1.05pu

Table 2 ANN training parameters

Parameters	Values
ANN type	Multi-layer feed forward
Test patterns	1215
Training patterns	5412
Maximum number of epochs	500
Output layer activation function	Linear
Hidden layer activation function	Hyperbolic tangent
Training algorithm	Back-propagation
MSE (mean square error) goal	0.1e-6

As input vector of 5412 data sets are applied to train ANN with a topology of 80-26-16-1 to detect the fault state of the HVDC systems. The output layer of the ANN can reduce the mean square error (MSE) to 0.22582E-4 within 53 epochs as illustrated in Fig. 3.

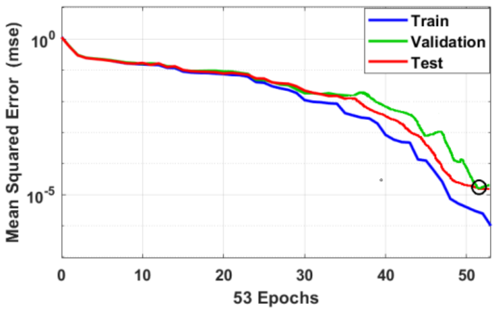

Fig.3. Fault detection ANN performance

For the proposed ANN fault classification. The training patterns of the post-fault conditions only are used to train the ANN fault classifier. The training patterns are consisted of about 4150 patterns representing different types of faults: pole to pole to ground fault, pole to pole fault, negative pole to ground fault, positive pole to ground fault, inverter side faults and rectifier side faults. These patterns are the post patterns applied previously to train the fault detection ANN. The output layer can reduce the ANN MSE to a value of 4.69E-4 within 57 epochs with ANN structure of 80-25-18-5 as shown in Fig. 4.

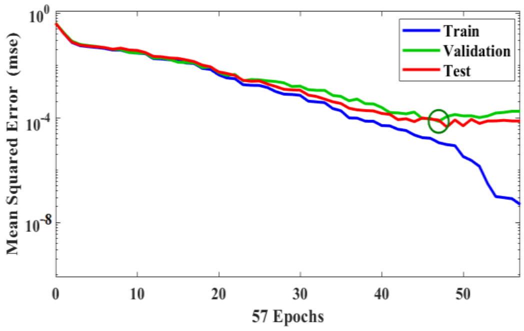

Fig. 4. Fault classification ANN performance

V. RESULTS AND DISCUSSIONS

5.1 Fault simulation results

The current input signals to the ANN must have different post and pre faults characteristics for different fault locations and types to manage ANN to decide about the conditions of the HVDC systems. The proposed ANN uses the average values of the current signals, so the DC current signals provided by existing meters is averaged. 20 samples of each current signal are delivered continuously to ANN as an input vector. The fault types that present in this paper are on the DC line, single pole to ground faults, pole to pole to ground faults and pole to pole faults while on the AC sides, three-phase, two-phase, and single-phase to ground faults. Those faults have different behaviour as explained for some fault cases in the following sections.

5.1.1 Positive pole to ground

A fault occurs at 20% of the HVDC system of type positive pole to ground. The resistance of fault is equal to 0.0001 Ω, power=1pu and VAC1=1pu. Figure 5 illustrates the measured current for pre and post fault. Where Fig. 5a shows the current in positive pole measured at the rectifiers side, Fig.5b illustrates the current of the positive pole measured at the inverters side, Fig.5c describes the current of the negative pole current at the rectifiers side, and Fig. 5d illustrates current of the negative pole current at inverters side.

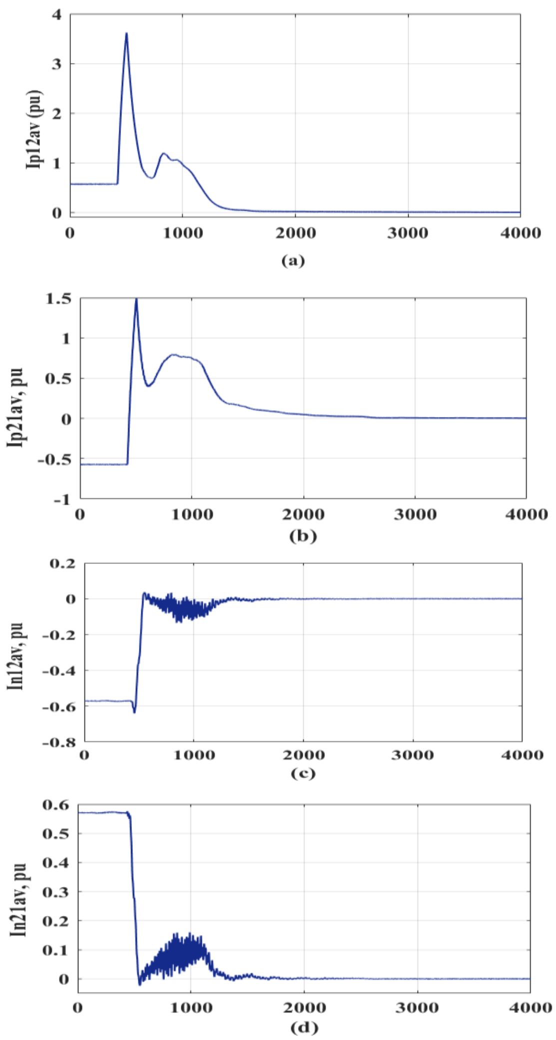

Fig.5 Positive pole-ground fault at 20% TL, (a) current in positive pole measured at rectifier side, (b) current in positive pole measured at inverter side, (c) current in negative pole measured at rectifier side, (d) current in negative pole measured at inverter side.

5.1.2 Negative pole to ground faults

A fault occurs at 35% of the HVDC system of type negative pole to ground. The resistance of fault is equal to 15 Ω, power is 0.8pu and VAC1 is 1.05pu. Figure 6 illustrates the measured current for pre and post fault. Where Fig. 6a shows the current in positive pole measured at the rectifiers side, Fig.6b illustrates the current in positive pole at inverters side, Fig.6c describes the current in negative pole current at the rectifiers side, and Fig. 6d illustrates current in negative pole current at inverters side.

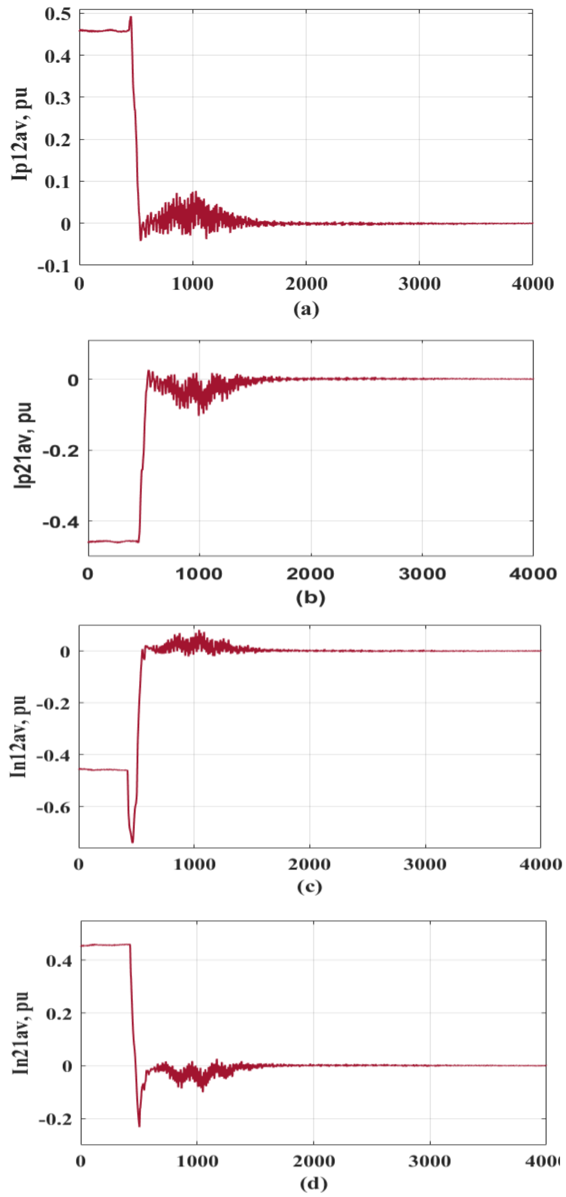

Fig.6 negative pole- ground fault at 35%TL, (a) current in positive pole measured at rectifier side, (b) current in positive pole measured at inverter side, (c) current in negative pole measured at rectifier side, (d) current in negative pole measured at inverter side.

5.1.3 For Pole to pole to ground fault

A fault occurs at 75% of the HVDC system of type pole to pole. The resistance of fault is equal to 5 Ω, power is 0.9pu and VAC1 is 1.0 pu. Figure 7 illustrates the measured current for pre and post fault. Where Fig. 7a shows the current in positive pole measured at the rectifiers side, Fig.7b illustrates the current of the positive pole measured at the inverters side, Fig.7c describes the current of the negative pole current at the rectifiers side, and Fig.

7d illustrates current of the negative pole current at inverters side.

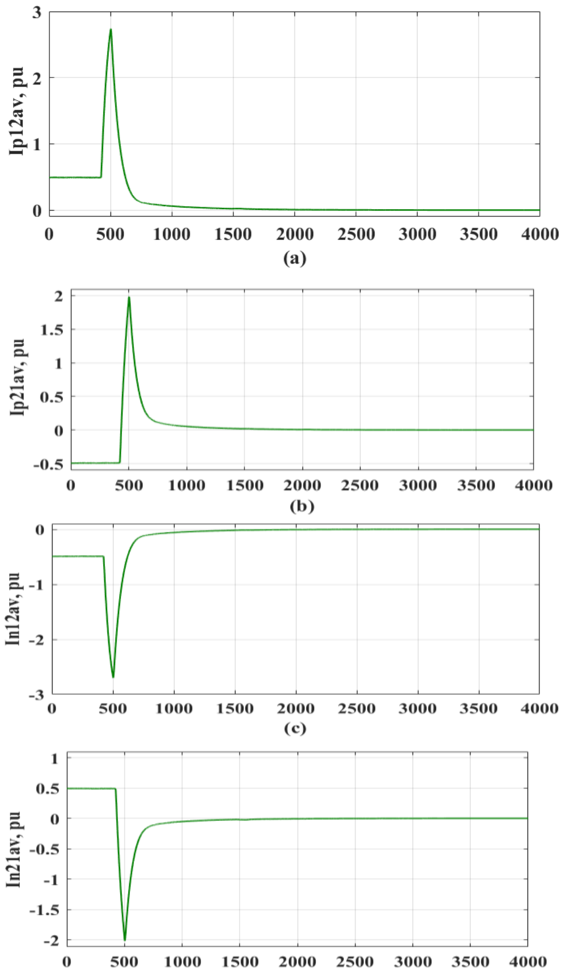

Fig.7 pole-pole-ground fault at 75%TL: (a) current in positive pole measured at rectifier side, (b) current in positive pole measured at inverter side, (c) current in negative pole measured at rectifier side, (d) current in negative pole measured at inverter side

5.1.4 Three-phase to ground faults

A fault occurs the AC side of the rectifier substation of type three phase to ground. The resistance of fault is equal to 5 Ω. Where Figure 8 illustrates the measured current for pre and post fault. Where Fig. 8a shows the current in positive pole measured at the rectifiers side, Fig.8b illustrates the current of the positive pole measured at the inverters side, Fig.8c describes the current of the negative pole current at the rectifiers side, and Fig. 8d illustrates current of the negative pole current at inverters side.

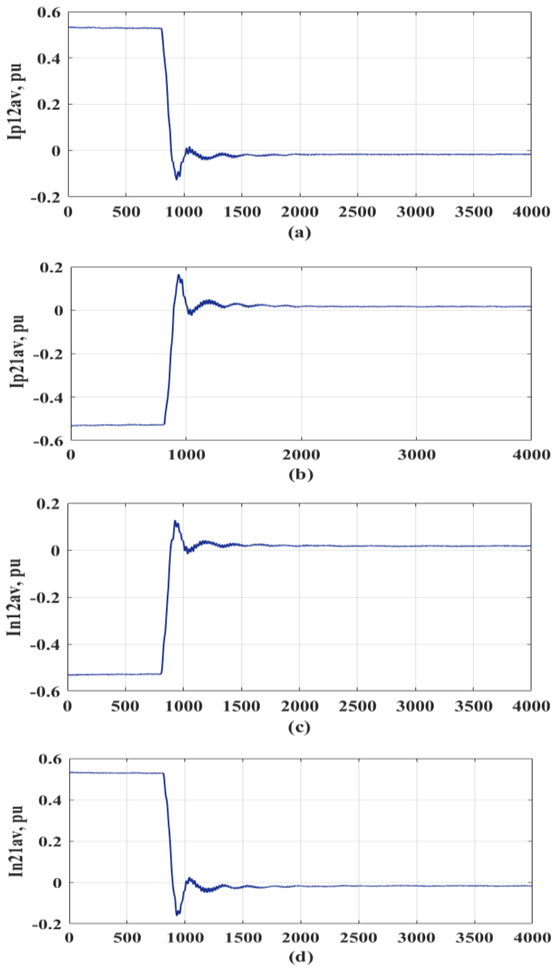

Fig.8 three-phase fault at rectifier substation: (a) current in positive pole measured at rectifier side, (b) current in positive pole measured at inverter side, (c) current in negative pole measured at rectifier side, (d) current in negative pole measured at inverter side.

5.2 ANN Fault detector performance

The optimum construction of the proposed ANN trained for 53 epochs by using the pre- and post-fault data patterns, consists of 80-26-16-1 neurons. The average detection accuracy obtained in each iteration is shown in Fig. 12. It is calculated from the data patterns for independent 25 runs. As shown in the figure, the performance of the proposed ANN is improved by increasing the number of iterations. Also, the proposed ANN is converged before reach the maximum iteration number. The test data patterns are detected with accuracy of 99.5%.

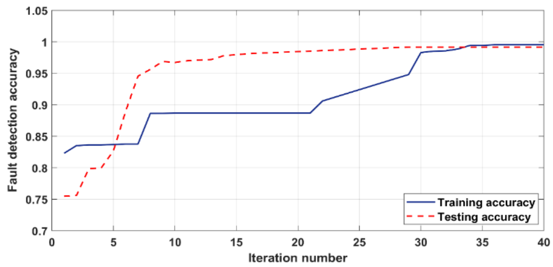

Fig. 12. Average fault detection accuracy of the ANN detector

Fig. 13 shows the confusion matrix of trained and tested results of data simulation. The true states are shown on the x-axis while the y-axis shows the estimated states. The main diagonal values represent the true detected cases.

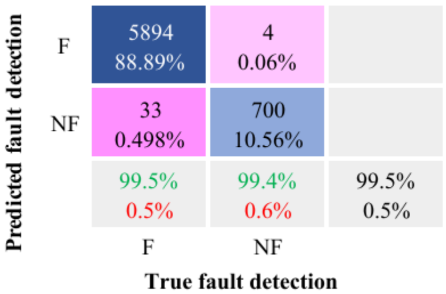

Fig. 13. Confused matrix for ANN fault detector

5.3 ANN Fault classifier performance

The accuracy of the ANN based faults classification is illustrated in this subsection. Six main different types of faults (pole to pole, double pole to ground, positive pole, negative pole, inverter side faults, and rectifier side faults) are applied to evaluate the ANN fault classification performance. The fault classifier ANN is triggered when a faut is detected by the ANN fault detector. In this case, 5927 patterns of fault cases are used to test the accuracy of the fault classifier. It trained for 53 epochs and the optimum network structure is 80-25-18-5.

The average accuracy of the ANN fault classifier obtained in each epoch is illustrated in Figure 14. The average accuracy of the classification is calculated from the dataset of the faults for 30 different runs. As shown in Fig. 14, the performance of the best-fitted ANN structure has become stable after thirty iterations. It can be shown also that the accuracy of the ANN fault classifier is about 98.62%.

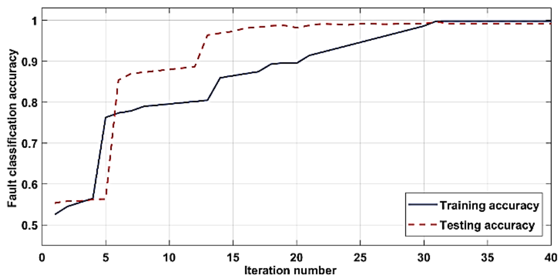

Fig. 14. Average accuracy of fault classifier

VI. Conclusion

This paper introduced a differential protection method for the HVDC systems using the multilayer feedforward neural network. An effective ANN based detection of faults in the HVDC systems, and an ANN based fault classifier were designed. various fault types, such as pole to pole, double pole to ground, positive pole, negative pole, inverter side faults, and rectifier side faults were applied to evaluate the ANN fault detector and classifier performance. The simulation results of the ANN based fault detector and classifier proved their capability to identify the state from the data patterns and accurately detect the faults and classify their types. Moreover, the results demonstrated the efficiency of the proposed ANN fault detector and classifier under various system conditions. The proposed networks had accuracy of 99.5% and 98.62% for fault detection and classification respectively.

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