

A Backpropagation Feedforward NN for Fault Detection and Classifying of Overhead Bipolar HVDC TL Using DC Measurements

Assad Abu-Jasser¹, Mahmoud Ashour²

¹Associate Professor, Electrical Engineering Department, The Islamic University of Gaza, Palestine, P.O. Box 108
ajasser@iugaza.edu.ps

²MSc of Electrical Engineering, Gaza Electricity Distribution Company, Palestine, mymar2500@hotmail.com

Abstract- This paper suggests the use of back-propagation feed-forward artificial neural networks (NN) for fault detection and classification in the high voltage direct current (HVDC) transmission line (TL). To achieve these tasks, post-fault measurements of the dc voltages and currents at the rectifier station related to the pre-fault measurements are used as inputs to the neural network. A bipolar HVDC TL model of 940 km long and ± 500 kV is chosen to be studied. This paper handles most frequent kinds of overhead bipolar HVDC TL power faults, and the results obtained are completely satisfactory.

Index Terms— HVDC Transmission Lines - Fault Detection - Fault Classification - NN - Feedforward-Backpropagation - Bipolar - Overhead - DC Measurements - Three Gorges Changzhou (3GC).

I INTRODUCTION

Electrical power is generated as an alternating current (AC). It is also transmitted and distributed as AC and apart from certain traction and industrial drives and processes, it is consumed as AC. But High-voltage AC transmission links have disadvantages, which may compel a change to DC technology, HVDC is preferred to use in the following categories [1]:

1. Transmission of bulk power where AC would be uneconomical, impracticable or subject to environmental restrictions.
2. Interconnection between systems, which operate at different frequencies, or between non-synchronized or isolated systems.

HVDC TL, which are growing in size and complexity, will be always exposed to failures of their components. In the case of a failure, the faulty element should be disconnected from the rest of the sound system in order to minimize the damage of the faulty element and to remove the emergency situation for the entire system. This action should be taken fast and accurately and is accomplished by a set of automatic protective relaying devices [2].

A Bipolar HVDC TL is one type of HVDC TL configurations which consists of two poles, each of which includes one or more twelve-pulse converter units, in series or parallel. There are two conductors, one with positive and the other with negative polarity to ground [3]. Figure (1) shows a bipolar HVDC System.

This type of HVDC TL can be exposed to different kinds of faults, the most frequent faults of them can be described as follows:

1. Positive Line to Ground Fault (+Ve/GND).
2. Negative Line to Ground Fault (-VE/GND).
3. Positive line to Negative Line Fault (+Ve/-VE).

4. Positive Line Open Circuit Fault (+Ve O.C).
5. Negative Line Open Circuit Fault (-Ve O.C).

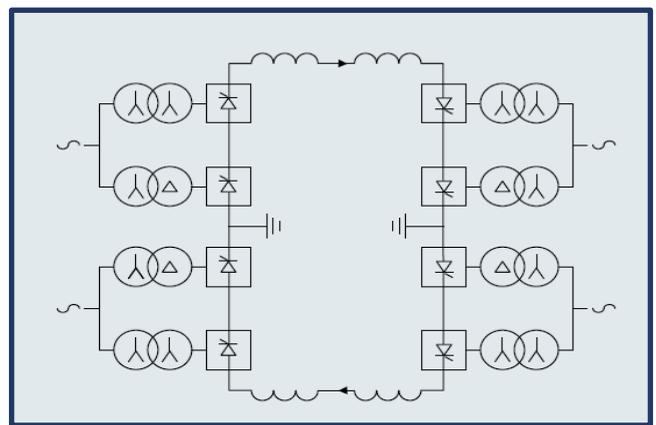


Figure (1): Bipolar HVDC System [3]

The identification and classification of faults is important for safe and optimal operation of power systems [4]. Neural Network technique is one of useful methods for detecting and classifying faults in HVDC TL since the nature of the outputs (finding faults and their classes) functional relationship is neither well defined nor easily computable. Furthermore, neural networks are able to compute the answer quickly by using associations learned from previous experience, gained either from time-domain simulations or previously gained practical experience [5]. Direct currents and voltages at the rectifier station are the most affected elements when a fault occurred in the HVDC TL and when the fault type changed. This characteristic can be used to detect and classify the HVDC TL faults by using the measurements of these voltages and currents as inputs to a NN.

In 1992, the use of NN to identify faults of AC-DC system with back-to-back HVDC construction was studied [6]. That paper focused on identifying faults of HVAC TL with probability of fault in back-to-back HVDC section. The researchers found a way to detect and classify faults but they do not handle dc faults and they only refer to them with (dc fault) without classification. In 1993, using NN in HVDC system faults diagnosis was studied [7]. A 20-12-4 NN structure was used to classify 16 different fault types for a six-pulse HVDC system. This paper focuses on detecting and classifying faults in AC-DC section and faults that may occur in the converter. In 1998, radial basis function NN was used for fault diagnosis in a HVDC system. The researchers used eight different inputs to classify five types of faults (four of them designated to classify AC faults). The researchers decrease inputs by using ground current instead of three currents of AC system [8]. As mentioned in previous papers the researchers did not handle HVDC TL section and they only referred to the faults in HVDC by (DC fault) without classification. In 2000, A new method to reduce the needed training data at the cost of time delay by using expert systems with NN to classify HVDC faults only. They use the same way that was used in 1998 to reduce inputs by using ground current. Expert knowledge was used to reduce training data. In that paper, inputs took as patterns with window length covers both pre/post fault regions [9]. In 2014, IEEE researchers used ANN for fault classification on HVDC systems and succeeded to diagnose HVDC faults. Here, NN output can predict the change in the firing angle required for the HVDC rectifier unit, where each value of the firing angle refers to special type of fault [10].

In this paper, the work will be focus on the faults of a HVDC TL link , not on the AC grid of the power system nor on the rectifier or the inverter stations. Depending on only four DC measurements , used as inputs to a special Neural Network, five types of most frequent faults ,that can expose to a twelve-pulse bipolar overhead HVDC TL, can be detected and classified precisely.

II ARTIFICIAL NEURAL NETWORKS

Neural Network (NN) can be described as a set of elementary neurons that are usually connected in biologically inspired architectures and organized in several layers [11]. The topology of a three layer feed-forward ANN is shown in figure (2).

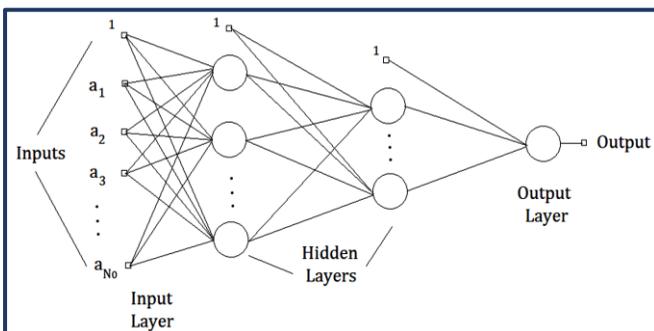


Figure (2): Basic 3 –Layer Feed-Forward NN [11]

There are N_i numbers of neurons in each I^{th} layer and the inputs to these neurons are connected to the previous layer neurons. The input layer is fed with the excitation signals. Simply put, an elementary neuron is like a processor that produces an output by performing a simple non-linear operation on its inputs [12]. A weight is attached to each and every neuron and training an ANN is the process of adjusting different weights tailored to the training set. An Artificial Neural Network learns to produce a response based on the inputs given by adjusting the node weights. Hence, we need a set of data referred to as the training data set, which is used to train the neural network.

III HVDC SYSTEM MODEL

The used HVDC system model was constructed in China, in 2003, to connect the land of Three Gorges with Changzhou (3GC). It is a 940-kilometre (580 mi) long, 3000 MW capacity, 12-pulse and bipolar HVDC transmission line. The (3GC) ± 500 kV DC Transmission Project is an integral part of the Three Gorges Hydroelectric Power Project. The DC transmission used to transmit the bulk power generated by this project to the Shanghai area in East China. The project interconnected the central power region of China to the eastern power region of China. The 3000 MW rated power have transmitted to a distance of 940 km on one single bipolar DC line at ± 500 kV. Figure (3) shows the single line diagram of 3GC [13]. The HVDC link is designed for continuous rating of 2×1500 MW under relatively conservative conditions specified for the system, ambient and outage. It has overload capability for temperature being lower than the extreme value, redundant cooling equipment being in service, and allowance in equipment design. The bipolar link has a continuous overload capability of 3480 MW and 5 second overload capability of 4500 MW. The nominal reverse power transfer capability is 90% of the rated power. The HVDC link is designed to operate continuously down to a DC voltage of 70% of rated voltage [14]. The HVDC system main component specifications summarized in table (1). Figure (4) shows the used HVDC network, this network was simulated by using MATLAB program, SimPowerSystem toolbox, and have been developed from [15].

IV STUDYING MODEL OUTPUTS

Many outputs can be detected from the studied model but the interesting is in the DC voltages and currents at the rectifier terminals. The network will be simulated with sampling time of 5×10^{-5} second for five types of faults each 3- and 5-km T.L long from the 15th km to 925th km and will be simulated many times for no fault cases. In each simulation the needed data will be registered to use it as neural network inputs. To study the power fault, the voltages and currents at the instant of fault doesn't give clear vision to make the neural network work properly. So, instead the data of voltages and current outputs must have a relation between post and pre fault data. The data of voltages and currents after one

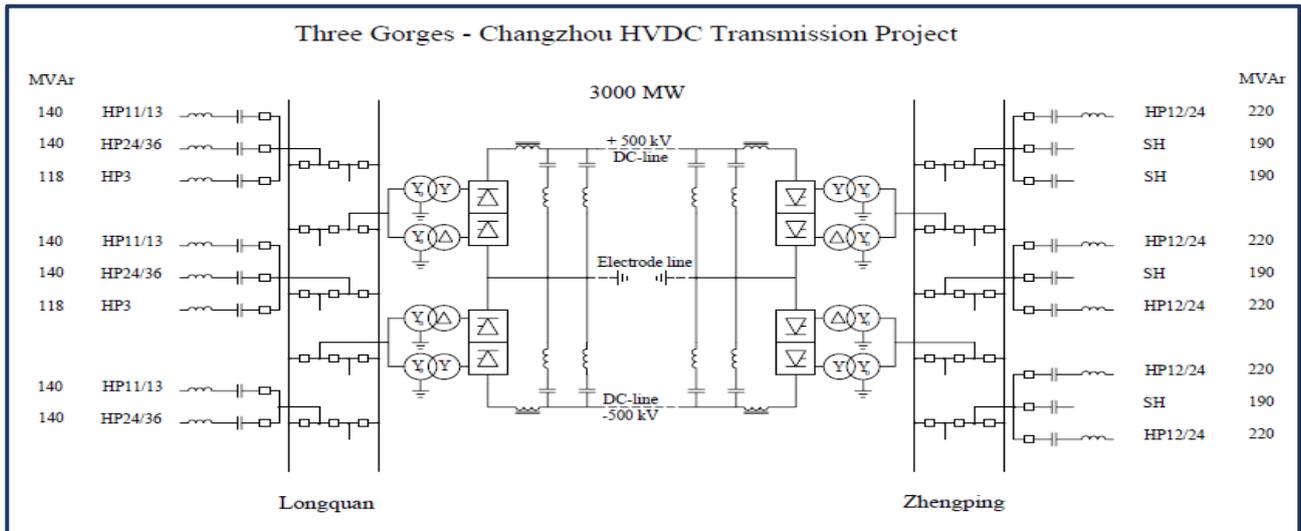


Figure (3): Three Gorges –Changzhou Single Line Diagram [13]

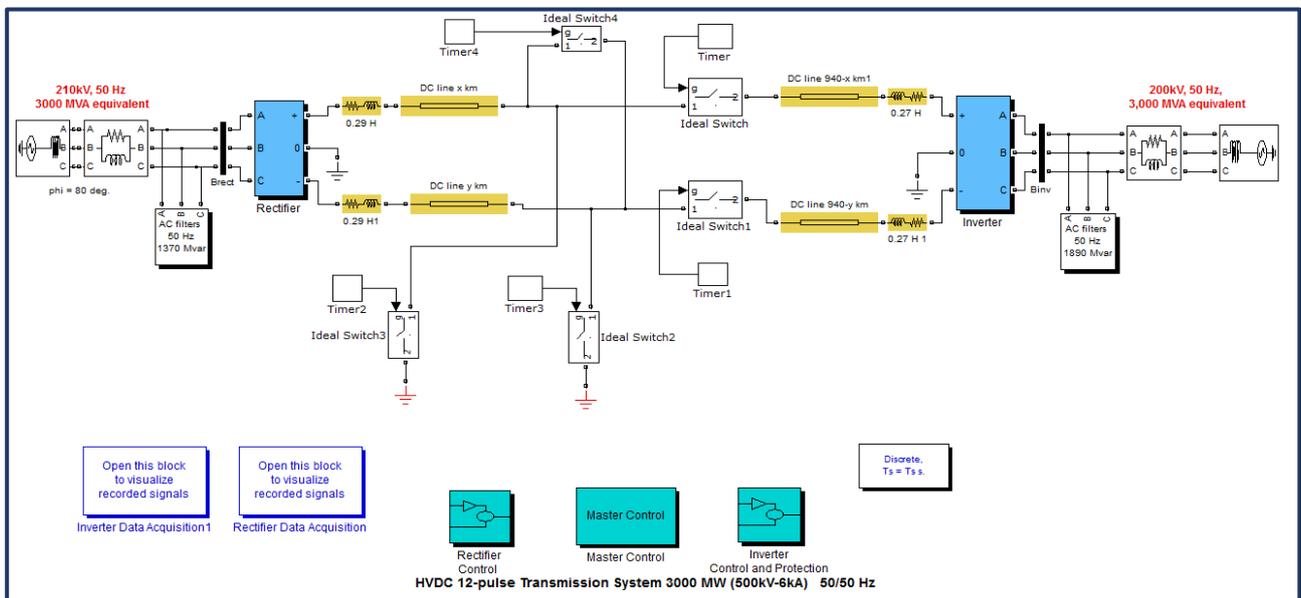


Figure (4): HVDC MATLAB Model

Table (1) Summarized Specifications of the System

Rectifier side							
AC Source				Converter Transformers			Smooth Reactors
Ph-Ph voltage	Internal resistance	Internal Inductance	Frequency	Type	Capacity	Voltages	Value
210.4KV	0 Ω	98.03mH	50 Hz	Single phase	297.5 MVA	525/210.4 KV	290 mH
Transmission Line							
Length		Resistance		Inductance		Capacitance	
940 km		0.015 Ω/km		0.792 mH/km		14.4 μF/km	
Inverter Side							
AC Source				Converter Transformers			Smooth Reactors
Ph-Ph voltage	Internal resistance	Internal Inductance	Frequency	Type	Capacity	Voltages	Value
200.4KV	0 Ω	28 mH	50 Hz	Single phase	283.7 MVA	500/200.4 KV	270 mH

cycle time of fault related to the data of voltages and currents before one cycle time of fault is used to represent the output data. This period is taken as reference to all measurements in this paper. Choosing of time period which takes as reference must be less than the adjusted protection system time to take all measurements in online environment. Using cycle time which is an AC period while the used measurements are in DC form is because of the effect of harmonics in that measurements. The used sampling time is 5×10^{-5} and the network frequency is 50 Hz, it means that each cycle needs 400 impulses to represent it. If the frequencies were different in both sides, the used frequency in simulation must be multiplier of both. The network outputs which are the NN inputs will be :

$$Outputs = \begin{bmatrix} V_{dc1}^* \\ V_{dc2}^* \\ I_{dc1}^* \\ I_{dc2}^* \end{bmatrix} = \begin{bmatrix} (V_{dc1} + 400)/(V_{dc1} - 400) \\ (V_{dc2} + 400)/(V_{dc2} - 400) \\ (I_{dc1} + 400)/(I_{dc1} - 400) \\ (I_{dc2} + 400)/(I_{dc2} - 400) \end{bmatrix}$$

Where:

- x+400 represents the value of x at 400 impulses after the instant of fault and x-400 represents the value of x at 400 impulses before the instant of fault.
- The 400 impulses represent a complete cycle in 50 Hz frequency and 5×10^{-5} sampling time.
- V_{dc1} : DC voltage of positive line at the rectifier DC side.
- V_{dc2} : DC voltage of Negative line at the rectifier DC side.
- I_{dc1} : DC Current of positive line.

I_{dc2} : DC Current of negative line.

V HVDC TL FAULT DETECTION

To detect faults; we must study the differences between the outputs of simulated model when the fault occur and when there is no fault. Table (2) shows model outputs of each type of faults at distances of 190-,375-,560- and 755 km away from the rectifier side and data in no fault cases. From table (2) each type of faults has special data. The no fault case is the normal case which has data of approximately ones. By studying DC data, we can compare between each type of faults and detecting the fault.

VI TRAINING AND TESTING OF DETECTION FAULT NEURAL NETWORK

To train neural network to detect existence of fault, 952 different cases for different types of faults and no fault type used as input for the neural network. The output of the neural network is fault exist with value of '1' and no fault with value of '0'. Many NN topologies have been trained to get the best performance, figure (5) shows the chosen 4-4-8-1 NN topology and the performance when uses Conjugate Gradient with Beale Powell Restarts training function. Best validation Mean Square Error (MSE) of 1×10^{-11} and gradient of 6.73×10^{-11} are achieved.

To test the chosen neural network 393 output of model simulation for conditions differ from the training conditions are used as input for the chosen neural network. The maximum error value between the NN outputs and targets is 7.3×10^{-7} (approximately no error).

Table (2): Model Outputs for various Fault Types and No Fault Conditions

Fault	+Ve/GND		-Ve/GND		+Ve /-Ve		+Ve O.C		-Ve O.C		No Fault
	190	375	190	375	190	375	190	375	190	375	
V_{dc1}^*	0.26	0.23	0.72	0.68	0.58	0.34	2.52	2.30	1.02	0.99	0.99
V_{dc2}^*	0.74	0.70	0.27	0.23	0.58	0.34	1.05	1.02	2.52	2.30	0.99
I_{dc1}^*	3.60	3.60	0.12	0.17	2.81	2.62	0.00	0.01	1.27	1.29	1.00
I_{dc2}^*	0.03	0.08	3.61	3.60	2.81	2.62	1.16	1.18	0.00	0.01	1.00
Fault	+Ve/GND		-Ve/GND		+Ve /-Ve		+Ve O.C		-Ve O.C		No Fault
Distance	560	755	560	755	560	755	560	755	560	755	
V_{dc1}^*	-0.25	0.07	0.72	0.69	-0.07	0.06	1.83	1.77	0.98	0.95	0.99
V_{dc2}^*	0.75	0.71	-0.25	0.07	-0.07	0.06	1.00	0.97	1.83	1.77	0.99
I_{dc1}^*	3.56	3.56	0.20	0.27	2.68	2.54	0.00	0.00	1.31	1.32	1.00
I_{dc2}^*	0.11	0.19	3.56	3.56	2.68	2.54	1.21	1.23	0.00	0.00	1.00

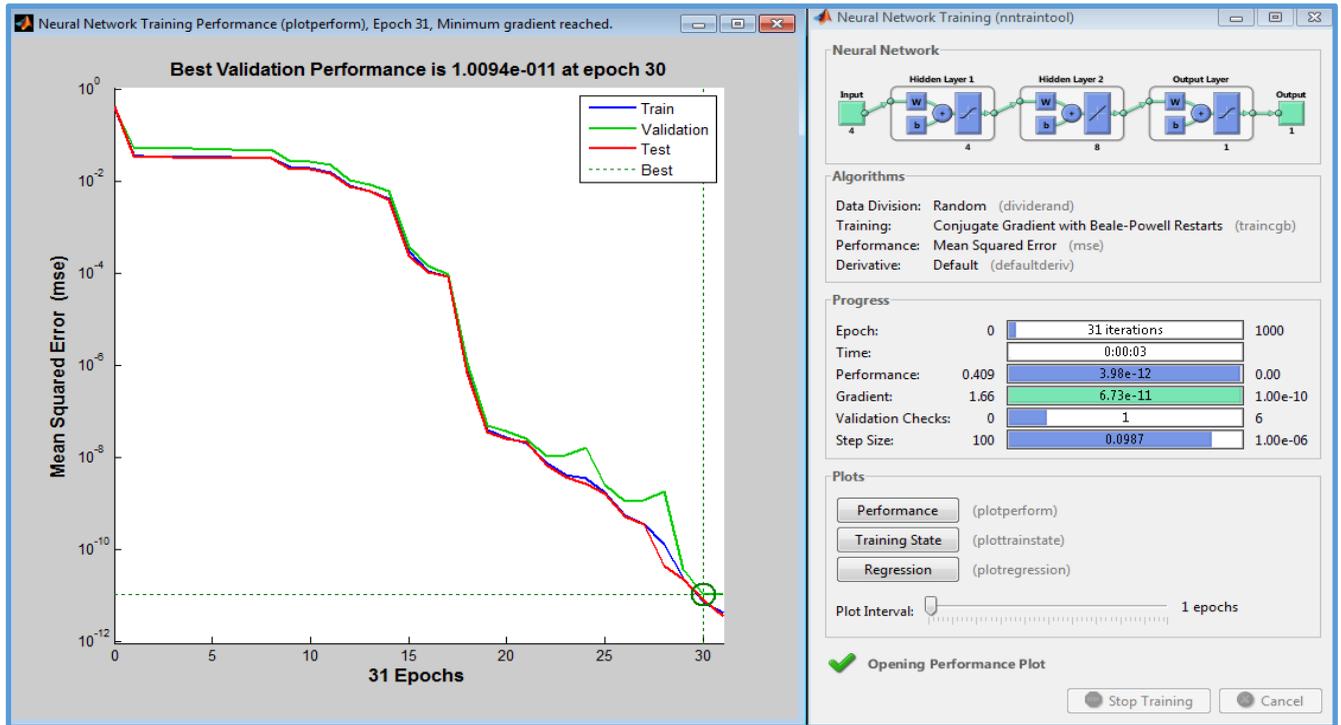


Figure (5): Fault Detection NN Performance

VII HVDC TL FAULT CLASSIFIER

After detecting fault, the next level of classifying that fault starts. Five types of faults are studied, each has a special code to represent it. Table (3) shows the fault types and their represented codes. Each digit in the code represents an output of NN. So, the used NN will be with 4 inputs and 3 outputs.

Table (3): Fault Types and their Codes

Fault	Code
+Ve/Gnd	001
-Ve/GND	010
+Ve /-Ve	011
+Ve O.C	100
-Ve O.C	101

VIII TRAINING AND TESTING OF FAULT CLASSIFICATION NN

For classifying HVDC TL faults a NN of **4-10-20-10-3** topology with Conjugate Gradient with Beale Powell Restarts training function was chosen , the best validation MSE of 8.8×10^{-12} was found. Figure (6) shows the 4-10-20-10-3 NN topology and its performance.

To be sure that we construct a powerful NN, 355 cases of different faults differ from the cases used in training the NN is used to test the NN. The maximum error in digits value of NN simulation outputs related to the target was 2.8×10^{-6} .

IX CONCLUSION

A feed-forward back propagation neural network has been constructed and trained for detecting and classifying most frequent types of faults on a bipolar HVDC transmission lines. The model employed to conduct the research is a 940 km long and ± 500 kV overhead bipolar HVDC line. The measurements of the DC voltages and currents at the rectifier side of HVDC system were used as inputs to the chosen NN to give four inputs, which monitored normally in the sending station and do not need special hardware. A four-layer NN of **4-4-8-1** topology was used to detect the existence of faults with a MSE of 1×10^{-11} in the training level and approximately no error when tested.

Five types of HVDC TL faults were classified by using five-layer network of **4-10-20-10-3** topology with a MSE of 8.8×10^{-12} in the training level and with no error when tested.

Using only four inputs to get all that results may be look not enough but all the trained and tested cases give no error when simulated. The used technique is easy, reliable and gives satisfactory results. The method is very fast and also works on-line and do not need more than a time of one cycle after fault occurrence to register the needed data. This time is less below that of a practical switch-off relay where the time needed is approximately the time of 3-5 cycles.

REFERENCES

- [1] HVDC for Beginners and Beyonds, Carl Barker, ALSTOM Grid Worldwide magazine, 2010.
- [2] Fault Location on Power Networks, Murari Mohan Saha, Jan Izykowski, Eugeniusz Rosolowski, Springer, 2010.
- [3] Design aspects of Korean mainland to Cheju island HVDC transmission, JL Haddock, FG Goodrich, Se Il Kim, Power Technology International, Sterling Publication Ltd p.125, 1993.
- [4] Identification of Faults in HVDC System using Wavelet Analysis, K.Satyanarayana, Saheb Hussain MD, B.Ramesh, International Journal of Electrical and Computer Engineering (IJECE), April 2012.
- [5] Fault Identification in an AC-DC transmission system using neural networks, N. Kandil, V.K. Sood, Transactions on Power Systems, Vol. 7, No. 2, May 1992.
- [6] Fault Identification in an AC-DC transmission system using neural networks, N. Kandil, V.K. Sood, Transactions on Power Systems, Vol. 7, No. 2, May 1992.
- [7] HVDC systems fault diagnosis with neural networks, L.L La1, F.Ndeh-Che, Tejedo Chari, The European Power Electronics Association, 1993.
- [8] Application of a Radial Basis Function (RBF) Neural Network for Fault Diagnosis in a HVDC System, K. G. Narendra, V. K. Sood , IEEE Transactions on Power Systems, Vol. 13, No. 1, February 1998.
- [9] Neural Network Based Fault Diagnosis in an HVDC System, H.Etemadi, V.K.Sood, K.Khorasni, R.V.Patel, International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, April 2000.
- [10] Classification of Fault Analysis of HVDC Systems using ANN, P. Sanjeevikumar, B. Paily, M.a Basu, M. Conlon, IEEE, 2014.
- [11] Artificial Neural Network Based Fault Location for Transmission Lines, Suhaas Bhargava Ayyagari, 2011, University of Kentucky.
- [12] Neural networks for optimization and signal processing, Cichoki A, Unbehauen R, John Wiley & Sons, Inc., 1993, New York.
- [13] Role of Three Gorges – Changzhou HVDC in Interconnecting Central and East China, Abhay Kumar, Yuan Qingyun , Shanghai Symposium , 2003.
- [14] Three Gorges - Changzhou HVDC : Ready to Bring Bulk Power to East , The 4th International Conference on Power Transmission & Distribution Technology 2003 14-16 October, 2003.
- [15] High Voltage Direct Current Transmission Arilaga, J., IEEE Power Engineering Series 6, Peter Peregrinus, Ltd., 1983.