Military Technical College
Kobry El-Kobbah,
Cairo, Egypt

6th International Conference
on Electrical Engineering
ICEENG 2008

Adaptive protection for series-compensated transmission lines using neural networks

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Abstract:

This paper presents an adaptive protection approach for classifying and locating faults in Thyristor Controlled Series-Compensated (TCSC) transmission lines. The proposed scheme is based on Multilayer Feedforward Neural Networks (MFNNs). Levenberg-Marquardt (LM) training algorithm is employed. The LM algorithm appears to be the fastest training algorithm and highly nominated for better generalized models. Three-phase power system currents and voltages at the relay location are used as inputs to MFNN-based relay. Two neural networks are trained to address fault classification and location. Feasibility and reliability of the proposed scheme are investigated using fault data set of a typical 500 kV power system simulated in EMTP-ATP package. Studied system is subjected to all possible shunt faults at different operating conditions, including fault location, fault inception angle and fault resistance. Simulation results demonstrate that MFNN-based relay system is very robust, fault tolerant, and highly accurate in protecting Flexible AC Transmission Systems (FACTS), such as transmission lines with TCSC.

Keywords:
Fault classification, Fault Location, Back-Propagation Neural Networks (BPNN), Thyristor-Controlled Series Compensated (TCSC) Transmission Lines, FACTS.

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1. Introduction:

Flexible AC Transmission Systems (FACTS) devices are used for dynamic control of voltage, impedance and phase angle of high voltage transmission lines with substantial improvement in power transfer, and transient and steady state stability margins. One of these devices is Thyristor-Controlled Series Capacitor (TCSC), which is capable of electrically shortening long transmission lines hence reducing transmission losses, and maximizing transferred power to the thermal limits of existing lines.

However, introducing TCSC to transmission systems makes the design of protection system a challenging task [1]-[3]. TCSC causes abrupt change in the impedance of the transmission lines, and creates new switching transients due to resonance between series capacitor and the power system inductance. In addition, the picture is getting worse if the over-voltage protection of series capacitor operates due to high fault currents. All of these effects contribute to the distortion of phase voltage and line current waveforms, and hence, most likely false tripping/blocking in conventional schemes-based protective relays.

A Kalman Filter approach [4] has been proposed for classifying and locating faults with respect to series capacitor. Nevertheless, the technique is sensitive to fault resistance.

Artificial Neural Networks (ANNs) offer an alternative solution for identifying and locating faults in power systems, since ANNs are able to extract characteristic features existing in input vectors. There have been previous attempts to use ANNs in protective relaying algorithms. Neural network and deterministic based approaches have been suggested for protecting series compensated transmission lines [5]-[6]. These techniques are based on compensating the capacitor voltage, and have limited operational success due to unpredictable performance of the Metal-Oxide Varistor (MOV) protecting series capacitor. Also, some schemes based on the Thyristor's firing angle have been reported [7]-[9]. Firing angle based algorithms are vulnerable to data transfer through communication channels in case of power lines with TCSC located at the midpoint of the transmission line. Travelling waves and Multilayer Feedforward Neural Networks (MFNN) have also been employed for detecting and classifying faults on power lines compensated at the two ends [10]. Yet, most of the work done so far has been based on utilizing the Thyristor's firing angle as an input to the NN-based relay. These techniques are susceptible to data transfer problems, and the firing angle information is hard to be obtained for practical closed-loop controlled systems.

The purpose of this paper is to report a reliable technique for fault classification and location in transmission lines with TCSC, using Multilayer Feedforward Neural Networks (MFNN). Proposed algorithm uses only power system voltage and current samples which are commonly available at the relay point. The improved LM optimizing training algorithm is robust in achieving global minimization of the performance function within a short numbers of training epochs.

This paper is organized as follows: section 2 covers studied power system, discusses the associated characteristic features for fault identification and location, and shows preparing training data and utilizing MFNN for adaptive distance protection. In section 3, simulation results are presented and discussed for validation of the proposed models. Conclusions are given in the last section.

2. Power System Study and Patterns Generation:

A. Power System Model

A two machine three-phase 500 kV, 60 Hz transmission system, as shown in Fig. 1, has been simulated for the study of fault classification and location problem. The power system comprises two sources, 160 mile transmission line, and TCSC with its associated protecting components located at the midpoint of the transmission line. The transmission line [11] has a positive-sequence impedance $\underline{Z}_1$=0.041+j0.528 Ohm/mile and zero-sequence impedance $\underline{Z}_0$=0.449+j2.02 Ohm/mile.

The TCSC is designed to work in capacitive vernier mode and to provide a variable compensation from 30% to 75%. The effective reactance of the series capacitor is governed by (1) [12]. Minimum compensation, 30%, is achieved at zero-conduction angle, while maximum compensation is obtained at a conduction angle of 62°. In this study, resonant factor, λ, is chosen as 2.5 for preventing resonance at characteristic harmonics, and providing smoothing control over the desired conduction angle range. Also, a Thyristor-Controlled Reactor (TCR) inductance, L_S, is selected at a value of 10.7 mH for providing a wider control range of σ. The performance of TCSC as a function of Thyristor conduction angle, σ, is depicted in Fig. 2. To avoid resonant region and provide compensation over the designed range, simulation studies have been performed for conduction angles in the range of 0° to 62°.

$$X_{TCSC} = -jX_C\left[1+\frac{2}{\pi}\cdot\frac{\lambda^2}{\lambda^2-1}\cdot\left\{\frac{2.\cos^2\left(\frac{\sigma}{2}\right)}{\lambda^2-1}\cdot\left(\lambda\cdot\tan\left(\frac{\lambda\sigma}{2}\right)-\tan\left(\frac{\sigma}{2}\right)\right)-\frac{\sigma}{2}-\sin\left(\frac{\sigma}{2}\right)\right\}\right] \tag{1}$$

Where σ is the Thyristor conduction angle, X_C is the reactance of fixed capacitor, SC, and λ is the resonant factor and is defined as the ratio of resonant frequency to power system frequency.

Figure (1): *one-line diagram of simulated power system model.*

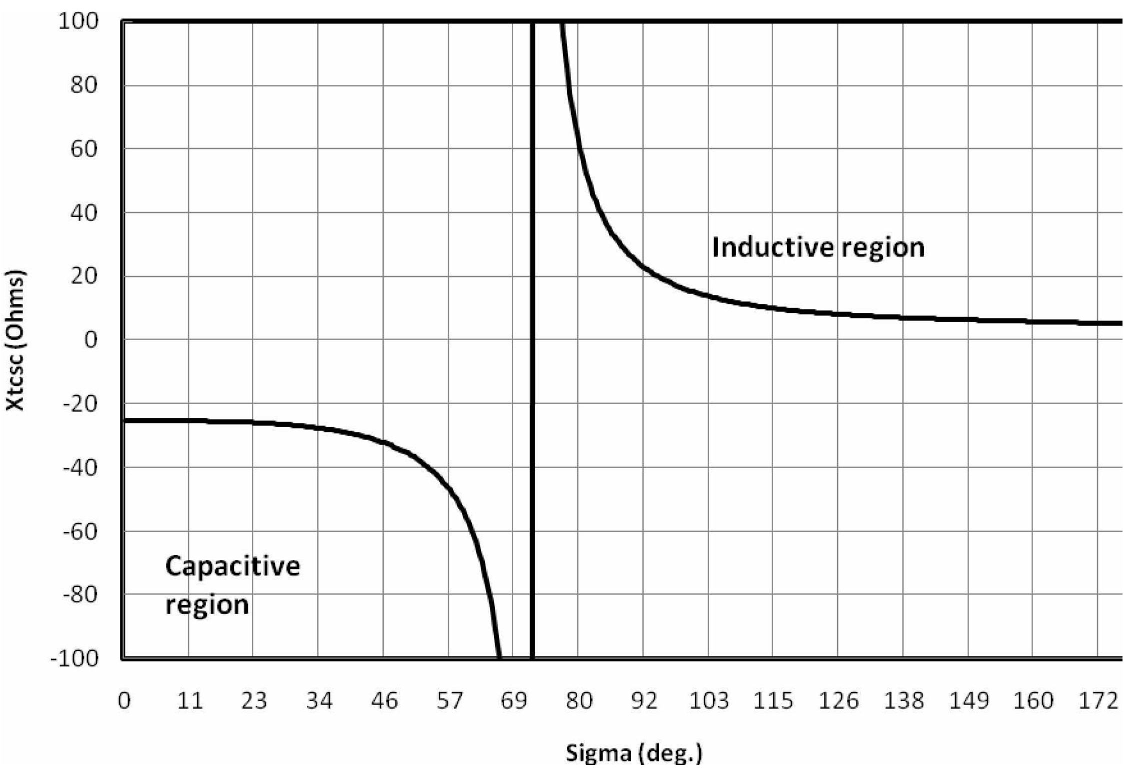

Figure (2): *Impedance characteristics of the TCSC.*

The TCSC is protected against overvoltage by a Metal Oxide Varistor (MOV). The MOV is represented by a single exponential model as:

$$i = p\left(\frac{v}{v_{pl}}\right)^{\alpha} \tag{2}$$

Where p and α are constants, and chosen as 1 and 30 respectively, V_{pl} is the protective level voltage of the capacitor and is selected at 120kV, which is two times the capacitor rated voltage. As long as the voltage across the capacitor is below the protective level, the MOV presents a very high resistance. When the capacitor is in the fault loop and capacitor voltage exceeds the protective level, the MOV resistance becomes low and it diverts part of the fault current away from the capacitor. Hence, the series capacitor is partially inserted in fault loop during fault period. If the fault is temporary, or the fault cause is cleared, the capacitor is automatically reinserted thereby enhancing power system transient stability. However, because of the non-linear characteristics of the MOV, the relationships between the voltage and current phasors are distorted and the distance relay could over-reach the fault.

Since the MOV is a non-linear resistive element and it has an energy dissipation limit, it is protected by monitoring the dissipated energy. If the MOV energy exceeds a pre-specified threshold value (5 MJ used in this study), a trigger signal is issued to an air gap to reroute the fault current away from the MOV. Depending on the fault type and fault resistance, the MOV/TCSC combination might be short-circuited within the first cycle, while fast protective relays are expected to make their decision. Then, the apparent impedance seen by the distance relay is distorted again and consequently the relay decision is unreliable. A bypass circuit breaker is usually incorporated to close the air gap when its energy limit is reached, and also for maintenance purposes. A small inductance, L_d, is used to limit the fault current through the air gap or the bypass circuit breaker.

From a practical prospective, transducers (current and capacitor voltage transformers or CT's and CVT's) represent a major element of any protective relaying scheme. They step down the high magnitude line currents and voltages of the power system to manageable level for driving protective relays. However, they could be source of error due to core saturation in CT's and transient response of CVT's. In addition to the CT saturation effect, in steady state, there is a CT ratio error because of the magnetizing current needed to establish the core flux. Thus, these aspects should be taken into consideration in fault studies. A typical current transformer of ratio 1200/5 with an accuracy of C100 has been modeled according to IEEE Std. [13]. Also, one of the capacitor voltage transformers reported in [14] is customized to match 500 kV studied power system.

The numerical simulations were performed using a well proven industrial program, Electromagnetic Transients Program (EMTP)-ATP software package [15]. The transmission line is represented by distributed parameters model. Since the TCSC distorts voltage waveforms, and line currents are free from harmonics because power lines are highly inductive, the line currents were used as synchronizing signals for generating stable firing pulses [12]. The firing circuits and MOV/protection circuitry have been simulated by Transient Analysis of Control Systems (TACS) components. Several fault scenarios including different fault inception times, fault types, fault locations have been simulated at a sampling frequency of 12 kHz. The power system voltage and current signals at the relay location are re-sampled at 960 Hz and retrieved for training/testing the proposed schemes.

B. Feature Extraction and patterns generation

Protective relay response is mainly based on defining the power system state through identifiable patterns of associated voltage and/or current waveforms. Therefore, the development of an adaptive protective technique can be treated as a problem of pattern recognition/classification. Neural networks are capable of classifying different patterns into favorite output classes through learning from examples. In the essence of pattern classification technique, it is important to select features that contain sufficient information needed to distinguish between classes, and permit efficient computation to limit the quantity of training data and the size of the network [7].

In practice, voltage and current waveforms measured by CVT's or VT's and CT's are readily available data at relay location. Moreover, they contain the entire information for monitoring abnormal conditions in power systems. Thus, scaled sampled voltage and current signals are usually used as inputs to digital protective relays. However, The post-fault current and voltage waveforms are accompanied with dc and high frequency harmonic components whose magnitudes depend on several random factors in nature. These harmonics need to be filtered out without jeopardizing the intrinsic information that might help in distinguishing different fault classes.

Through extensive fault studies of the selected power system shown in fig. 1, it is observed that post-fault current and voltage waveforms for faults before the TCSC are rather different in harmonic contents than those for fault loops involving the TCSC [4]. When a fault is initiated before the series capacitor, the dominant frequency components include: exponentially decaying DC component, high frequency components due to resonance between shunt capacitance and line inductance, and fundamental frequency component. On the other hand, the dominant frequencies for faults after the series capacitor include all previous harmonic components as well as additional non-fundamental harmonics due to resonance between power system inductance and series capacitor, and odd harmonics as a result of MOV conduction.

The protection system, as illustrated in fig. 3, is composed of classification and fault locating modules. Local samples of the three phase voltage and current waveforms were acquired from EMTP/ATP software at 12 kHz. All possible ten (10) shunt faults at different operating conditions and variations in fault location, fault inception time, power flow direction, and fault resistance were simulated. High fault resistance up to 100 Ω was considered. Twenty (20) samples of each waveform after fault inception were retrieved for training/testing purpose. These samples were preprocessed by 2nd order low-pass anti-aliasing filter and re-sampled at 960 Hz (16 samples per cycle), which is commonly used in numerical relays.

Voltage and current samples were linearly normalized to have a maximum value of +1 and a minimum value of -1. This was done by using a scaling factor of the peak value of the nominal voltage and twelve (12) times the rated current. Different scaling factors were used to maintain the same weighting for both voltage and current signals. In addition, scaling can speed up the training process and enhance the NN performance. Processed voltage and current samples were then used for generating labeled patterns.

Figure (3): Modular proposed protective scheme; ANN_{FC} is the fault classification module, ANN_{FL} is the fault location module.

3. Protective scheme using Multilayer Feedforward Neural Networks (MFNN):

A. Multilayer Feedforward Neural Networks (MFNN)

An intelligent machine learning technique, artificial neural network, provides an alternative concept to mathematical algorithms based on a series of programmed instructions. Since neural computing is expanding in the engineering field, different NN paradigms have been developed, e.g. a Multilayer Feedforward NN, Self-Organizing Mapping (SOM) NN, Radial Basis Function NN (RBFNN), and a Recurrent NN. The first type shows extraordinary advantages in learning underlying relationships from examples representing the problem at hand, capability of generalization even in noisy environment, and the ability to map nonlinear relationships existing in input vectors owing to its inherent nonlinearity [16]-[17]. In addition, the MFNN is widely applicable in different engineering disciplines.

The MFNN is a composite of elementary processing elements (neurons) arranged in multiple layers, i.e. input layer, hidden layers, and output layer. The neural networks are usually characterized by the activation functions of their neurons, neuron interconnection relationships, and the training algorithm.

Several techniques have been developed to speed up the convergence of Back-Propagation (BP) algorithm, which is commonly used for updating weights and biases of MFNN. One of these techniques is the Levenberg-Marquardt (LM) optimizing training algorithm [18]. The LM is based on updating the weights as,

$$W_{k+1} = W_k - [J^T J + \mu J]^{-1} J^T e \tag{3}$$

Where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The scalar μ is decreased after each successful step and is increased when a tentative step tends to increase the performance function. Thus μ is utilized to assure that the performance function (mean-squared error between targets and actual outputs) is always reduced at each epoch of the algorithm. This algorithm is selectable within the neural networks toolbox of MATLAB software [19].

For better performance and fast convergence, weights and biases of the network were initially assigned random values within the range [-1, 1] and the learning factor, μ, was given a value of 0.05. Then, the training input vectors were presented to the network in "batch" mode and the network's weights updated according to (3). The training process stopped when the validation error started to increase after reaching a minimum value. This stop validation criterion is used to prevent the network from memorizing and thereby enhancing the generalization capability.

B. Proposed MFNN Based fault classification

Data window is a key factor in designing NN structure and has great effect on its performance. Long data window enables protective algorithms to get more information resulting in stable performance, but slow decision can be achieved. After studying the simulation results and maintaining compromising performance, a data window of a quarter of cycle at 960 Hz sampling frequency was found to be sufficient for classifying all shunt fault types. A total of 7,650 labeled patterns were generated; each pattern consisting of twenty four (24) inputs – four samples for each of the three phase voltages and currents, and four (4) outputs representing three-phase and ground states. Each target output is assigned a value of +1 if the phase or ground is included in the fault and -1 otherwise. For example, if the output set {abcg} is equal to {1 -1 1 1}, it means that a 2-Φ to ground fault (a-c-g) is declared.

The total patterns were divided into three sets such that 60% were used for training, and 20% were used to validate and prevent the network from over-fitting the problem. The last 20% were used as an independent set to test the network generalization. Each set was shuffled in such a way that the network output alters between +1 and -1, and in turn precluding the network from learning specific sequence.

As the issue of selecting optimal number of hidden neurons is still evolving, an extensive series of studies on several network topologies has been conducted. Networks having 10, 12, 14, 16, and 18 neurons in the hidden layer were studied. Each network was trained as explained in section A. The network with 12 neurons in the hidden layer seemed to have the best performance. Different activation functions were evaluated. The Tan-sigmoid activation function for both hidden and output neurons was found to be the best suited for this application.

Mean-square error between the actual and desired output reached a minimum value of 0.01.

To evaluate the speed, generalization, and fault tolerant of the fault classification network (ANN_{FC}), several shunt faults were simulated and presented to the trained network. The ANN_{FC} was capable of detecting and classifying faults within an average time of 3 ms. Fig. 4 shows the three-phase voltages and currents and the network output for a 2-Φ fault, a-b, which occurred on the studied power system and located at 90 mile away from the relay point.

C. Proposed MFNN Based fault location

After studying the simulation results, it was concluded that fault location can be estimated using the readily available information at the relay point, which are voltage and current waveforms. Since data window length is a key factor in determining the network topology and performance, several data windows were tested and a half-cycle data window was found sufficient for locating shunt faults with respect to series capacitor. Training data included total of 6,552 patterns. Each pattern consisted of a vector of forty eight (48) elements, eight samples for the three phase voltages and currents, and one desired output indicating the fault location. The entire data was divided into three sets. Sixty percent of the data was assigned for training, while the rest forty percent was equally divided for validation and testing. Also, each of the sets was shuffled such that target output alters between +1 and -1.

As output of the NN indicates whether the series capacitor is included in the fault loop or not, one output neuron was used. A fault loop including series capacitor was indicated by an output of +1, while that excluding the series capacitor was indicated by -1. Number of input neurons was limited to the number of elements in input vector, but number of neurons in the hidden layer was determined by experimentation. Different network configurations were trained and tested. The LM training algorithm was used to reach the optimal weights and biases. The network finally selected for fault location problem had 48 neurons in the input layer, 10 neurons in the hidden layer and 1 neuron in the output layer. Tan-sigmoid activation function was used for hidden and output neurons because it showed better convergence for performance index function. Generalization capability of the selected network was assessed by presenting all patterns to each network and performing linear regression between network's outputs and corresponding targets. A mean-square error of 0.04 and R-value of 0.956 were reached. Thus, the selected network is most likely to accurately locate shunt faults.

A set of tests covering typical fault scenarios which were totally different from those used in training phase was simulated. The ANN_{FL} has been capable of locating faults with acceptable accuracy. The network's output for different fault types on transmission line at 20 miles from the relay point is shown in fig. 5. The network identifies accurately that the series capacitor is not included in the fault loop. Also, as depicted in fig.6, the network output is stable at +1 when the fault occurred at 100 miles from the relay location which included the series capacitor in the fault loop.

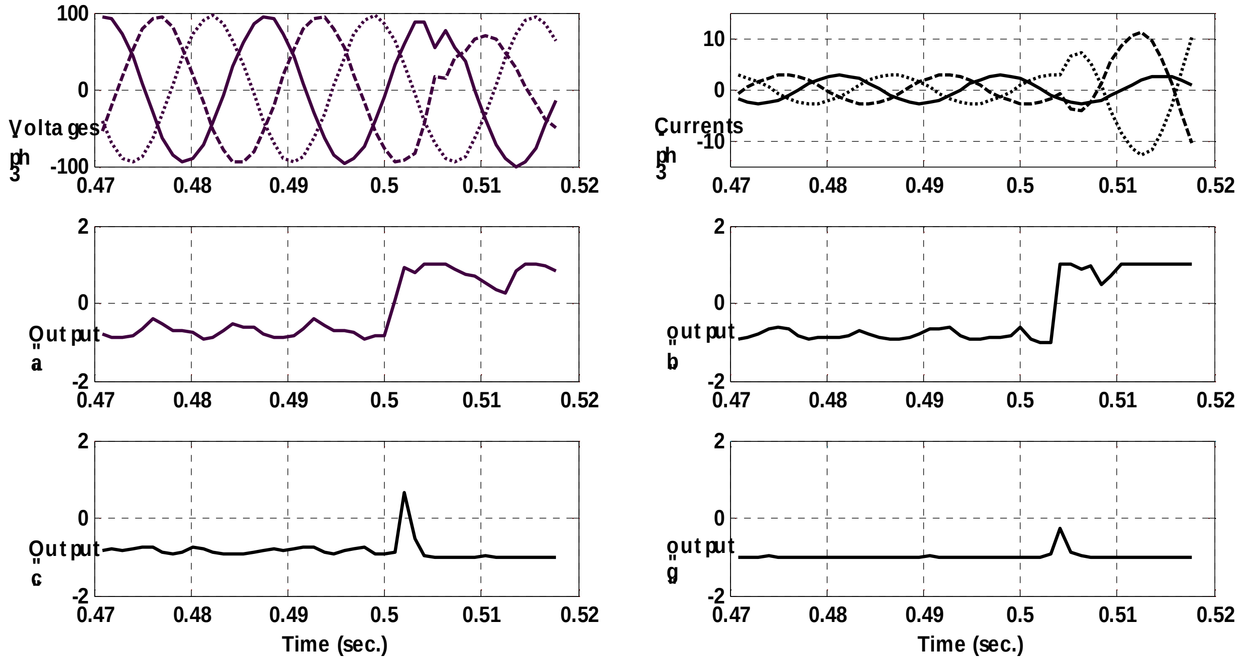

Figure 4: Fault classification network output for a-b fault at 90 miles, fault resistance 50 Ω, conduction angle 50°, δ= -10°, fault inception angle is 90°.

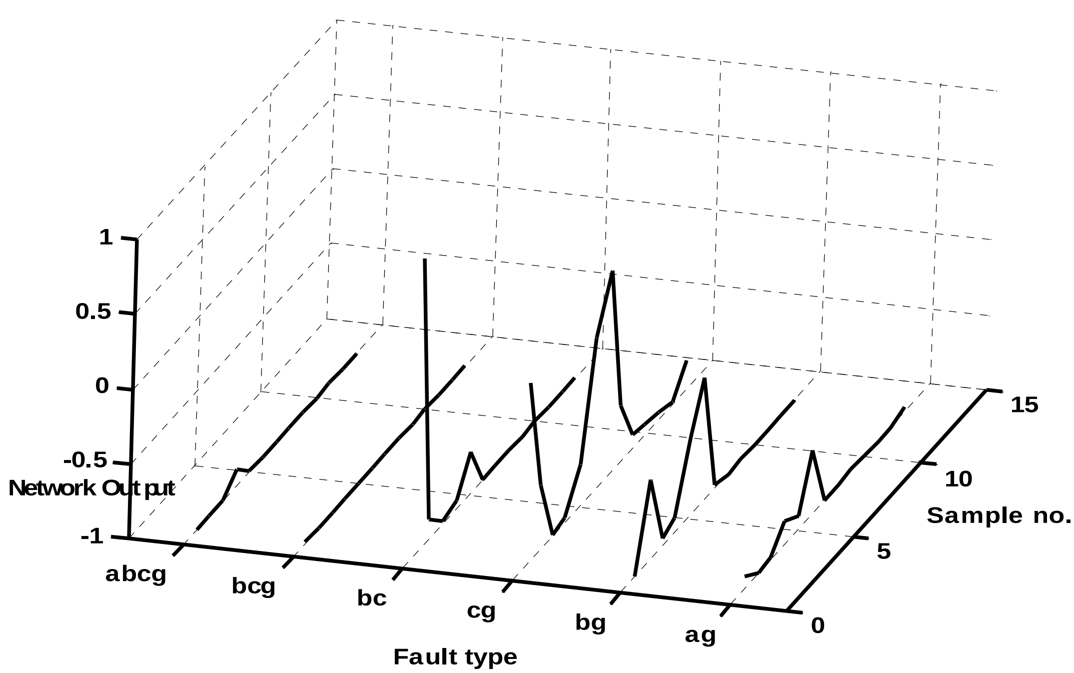

Figure 5: Fault location network output for faults at 20 miles, fault resistance 20 Ω, conduction angle 62°, δ=-20°, fault inception angle is 90°.

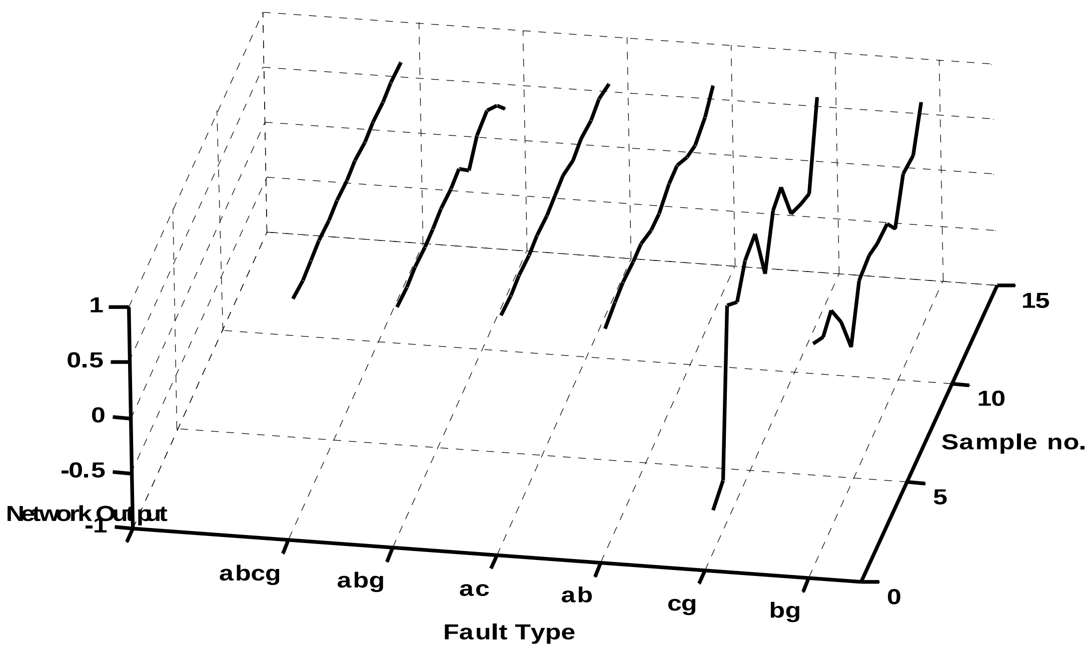

Figure 6: Fault location network output for faults at 100 miles, fault resistance 50 Ω, conduction angle 45°, δ= -10°, fault inception angle is 0°.

4. Conclusion:

This paper reports on the development of an ANN-based fault classification and location relay protection system for Thyristor-Controlled Series Capacitor (TCSC) transmission lines. Fault classification and location schemes use local end samples of power system voltages and currents to make a decision. Fault location scheme is designed to locate faults with respect to series capacitor, and is independent of the Thyristor's firing angle, α. This flexibility feature confirms that proposed algorithms could be realized for protecting series compensated transmission networks. For fault location, half-data window was found the best to reach a reliable decision. Proposed approaches were extensively tested for data set unseen in training phase. Simulation results show that proposed schemes are highly accurate and robust in classifying and locating all possible faults irrespective of fault resistance, MOV operation, pre-fault loading, and compensation degree.

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