Adapted Auto_Reclosing Relay In a Simulated 400Kv Grid

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Abstract— In this paper the concept of Artificial Neural Network (ANN) was implemented in constructing an Adaptive Single Phase AR (ASPAR) relay. The heart of this relay is an ANN trained to discriminate healthy system, permanent fault, transient fault and extinguishing of the secondary arc. Thus issuing right decisions. The proposed ANN method is trained only to recognize single phase to ground fault types (both transient and permanent) simulated on TL Model between Baijie Thermal Power Station and Mosul Super Grid Sub-Station 400Kv from Iraqi North Regional Grids (INRG).

Keywords— Adaptive Auto_Reclosing, ANN, Non Discriminating Protection (NDP), Matlab power syetem simulink.

I. Introduction

Auto_Reclosing (A/R) relay is one of the important protections in HV networks, which restore Transmission Lines after transient faults[1-3]. Specially most of the faults on Over Head Transmission Lines (OHTL) are transients in nature [4]. So A/R affects stability and improves reliability of the transmission system [5, 6]. Fig. 1 gives a general single line diagram of the lay out of A/R with Distance relay protection. Over the last two decades, a large number of researches and papers have appeared in the area of AI in power system protection [7-9].

Some particularities of Automatic Reclosing application in Russian electric networks in new conditions caused by the former USSR Separation are briefly characterized in [8], with a statistical data proving A/R effectiveness are given.

A Numerical Algorithm for Blocking A/R During Permanent Faults on Overhead Lines were proposed by [9]. The algorithm proposed in this paper determines the nature of the fault from the arc voltage amplitude estimated using the least error squares technique and blocking Auto_Reclosing relay during permanent faults. Simulation and laboratory results are included.

Development of Novel Adaptive Single-Pole Autoreclosure Schemes for Extra High Voltage Transmission Systems Using Wavelet Transform Analysis, have been proposed in [10].

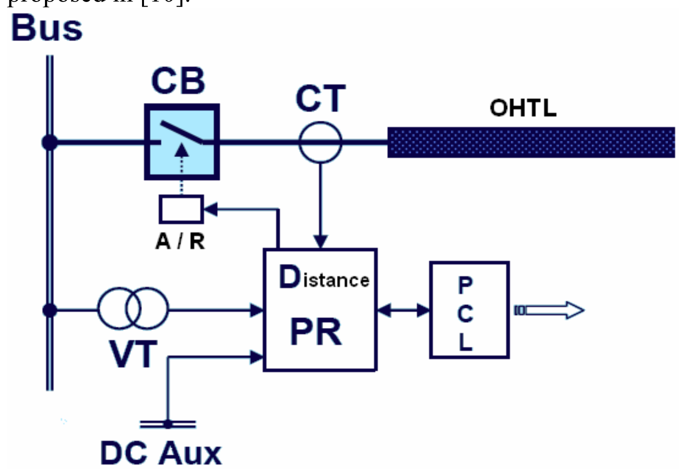

fig. 1: configuration of Transmission Line Bay in HV S/S.

The discrete wavelet transform is adopted to analyze the fault transients caused by the secondary arc and permanent faults. It is shown that certain wavelet components can be effectively used to detect and identify the fault characteristics.

II. Conventional A/R Scheme Description

Where the system cannot remain out to along periods the use of A/R is predominately employed by most supply authorities [4]. The three phases of the circuit-breaker are arranged to operate together, not only the faulty phase or phases are tripped and reclosed; the three phases tripped and reclose; if on reclosure it is found that the fault persists, the second trip opens all the three phases, and isolates the line completely with blocking the A/R Relay from operation until reclaim time setting valid [3].

III. Artificial Neural Network (ANN)

ANN method is used because it is simple and quite suitable to the problem of A/R protection than other AI methods [7].

A. *Model Implementation*:

Manuscript received March 20, 2009: Revised version received April 30, 2009. This work was supported in part by the Ministry of Electricity/ Iraq.
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Power system block set has been implemented by means of Matlab-Simulink. For the investigations of the effects of the secondary arc on the “dead time” of the single phase Auto_Reclosing relay operation. Matlab is a high-performance language for technical computing. It integrates computation,

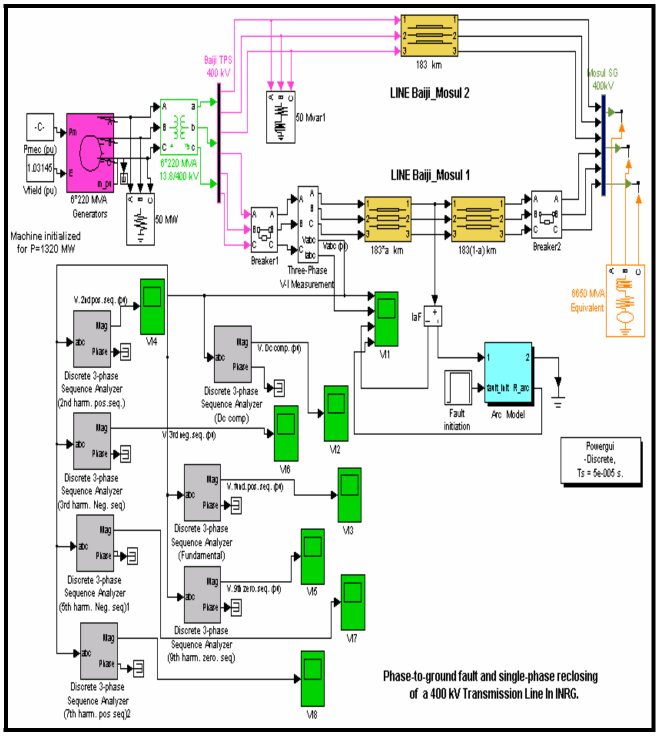

Fig. 2: Simulated Model of Mosul SG-Baijie.

visualization, and programming in an easy-to-use environment where problems and solutions are expressed in familiar mathematical notation [10]. Matlab Simulated power System block sets used to simulate the Iraqi North Regional Super Grid (INRSG). Two Lines between Mosul SG and Baijie 400 KV Sub Stations, of the types twin conductor per phase, each three phase conductors horizontally aligned and one circuit on single tower configuration. So there is no mutual effect between the two circuits. Both S/S’s Bus Bars (BB) have been represented. Baijie Power plant BB represented by the load Generated behind it, while Mosul SG BB, by the short circuit level on it’s 400 Kv BB.

TL’s parameters were simulated, using the equivalent pi cascaded sections, representing transposed TL, in which the mutual coupling effect is considered. The simulated circuit of Iraqi transmission system shown in fig. 2. TLs parameters given in Table I. Single phase to Ground faults are simulated on Mosul – Baijie No(1). The protection system at both ends pick-up and initiate

Table I: Super Grid 400 kv TL parameters:

TL Type	R1 ohm/km	Ro ohm/km	L1 mH/km	Lo mH/km	C1 nF/km	Co nF/km
Twin AAAC	0.034	0.27	0.001	0.0062	11.111	7.05

circuit breakers trip, in this case only the faulty phase will be isolated, the other two healthy phases will continue on service while the recommended power will flow through the parallel circuit (Mosul- Baijie No.2), and also through the shadow HV transmission Network; this is to maintain synchronism and increase the reliability & stability margin of the system.

There will be induced voltage in the faulty phase due to the current flowing in the sounded phases according to the mutual phenomena [1]. This voltage will feed the secondary arcing current via the fault path.

B. Circuit description:

Two 400 kV parallel lines, each of 183 km long, single circuit configuration, capable of transmitting 2000 MW of power from a generation plant (6 generators, each of 220 MVA) to an equivalent network having a short circuit level of 6650MVA. The generation plant is simulated with a simplified synchronous machine of Sub Transient reactance of 0.22 pu. As shown in fig. 2, the machine is connected to the transmission network through a 13.8 kV/ 400 Kv Star-Delta transformer. Line Baijie _Mosul 2 is shunt compensated by a reactor of 50 MVAR, connected at Baijie BB.

C. Arc Model

The arc is modeled by a fixed or non-linear resistance $R = f(I_{arc\_rms})$. It extinguishes when it’s rms current falls below a certain threshold value (typically 20 A) defined in the arc model block. Actual arc extinction occurs at next current zero-crossing [11]. The mean arc resistance is programmed as an exponential function of the rms current, and it’s resistance increases when the rms arc current decreases so that the time for arc current to decay below the threshold value is shortened.

The fault is applied at t = 20 msec. Then, the opening command is sent to both breakers at t = 80 msec (3 cycles time for fault detection +1 cycle for CB opening time), then the two CBs are Reclosed at t = 34 cycles time after a dead time of 30 cycles time, during which the arc creating the fault should be extinguished.

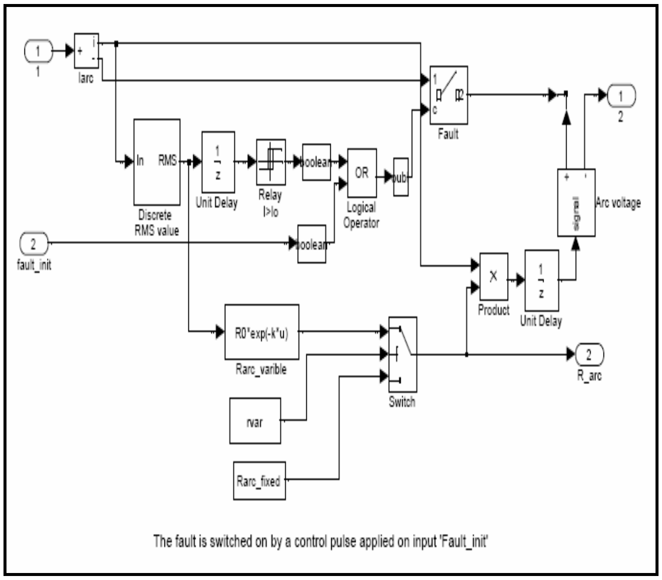

Fig. 3: Arc model simulation block [10].

IV. Feature Extraction

Feature extraction is the process of selecting out from a range of possible data measurements the data which will be used to represent the problem, and whether this data will require transformation into different form [12]. The choice of feature extraction method is problem dependent.

A. *Faulted phase voltage analysis*

The voltage waveforms from the faulted phase are measured along the simulation time. So discrete values of the voltage prior to fault inception and when the circuit breakers have subsequently tripped at both ends of the line along with secondary induced voltage wave forms are included. An array of data from the time domain contains information implicitly in the ordering of the data. There is no phase synchronization associated with measuring the voltages, so the absolute phase values of the signal components are not relevant.

B. *Classification*

Each window Xn can be associated with an output class. In the Adaptive Single phase Auto_reclosing ASPAR cases considered here the output classes are:

Class 1: Do not reclose

Class 2: Safe to recluse

1) *Class 1, (Do not reclose):*

Class 1 wave shapes occur when there is either a permanent fault, or there is a transient fault which is still in the stages of secondary arcing. These situations are shown in Fig. 4 and 5 simultaneously. Refer to fig. 4, it is an example of a permanent fault waveform of a constant impedance bolted fault. The fault incepts at position A on the waveform, and the circuit breakers open at point B. The signal is then a member of the class 1 of do not reclose. Where as fig. 5 representing a transient fault but in secondary arcing stage. This also represents a window from class do not reclose and it needs a time to distinguish the secondary arc current and regain the dielectric properties of the air insulant. sufficiently to withstand the restoration of full system

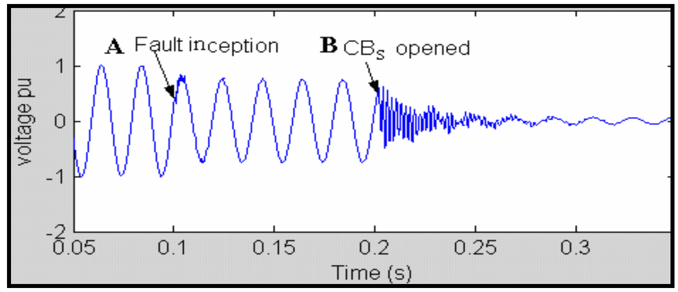

Fig. 4: Permanent Fault from class 1.

2) *Class 2, (Safe to reclose):*

This case represents a nominally healthy phase voltage which may occur due to an incorrect trip event or a post secondary arc of transient fault. This condition is shown in Fig. 5. As can be noted from fig. 5 & 6 that it is a transient fault in the first case, the second class does not allow within the time required for an arc path to de-ionise sufficiently that help withstand the restoration of full system voltage. The classification of data windows into these classes therefore requires some form of decision support and algorithmic consideration before being acted upon by a relay.

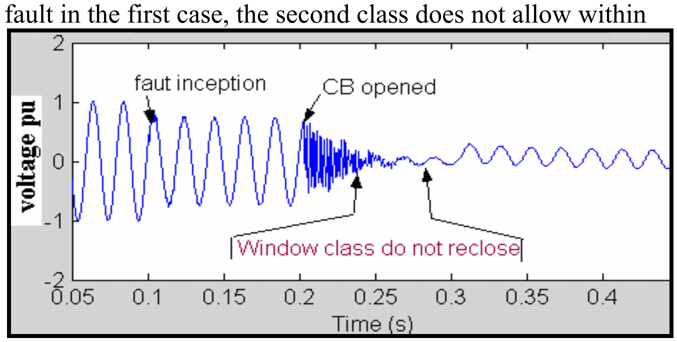

Fig. 5: Transient fault with window from class1.

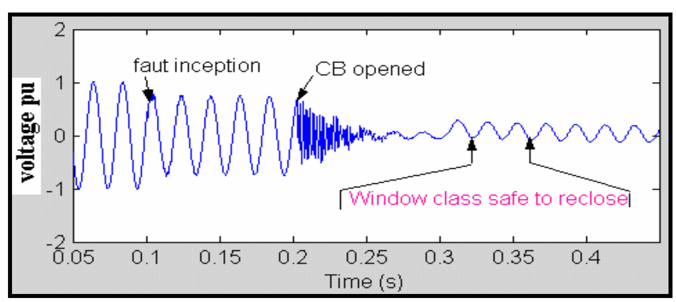

Fig. 6: Transient fault with window from class 2.

IV Frequency and Amplitude Analysis

The voltage signal taken from the faulted phase of the transmission line varies with time, and the frequency components within the waveform evolve with time during the progression of the fault. Fast Fourier Transform (FFT) analysis which take an input array and product a frequency domain representation are a powerful technique for examining the behavior of sequential wave form. The basic premise of a frequency domain representation is that the signal can be fully represented, over an interval, by the superposition of a number of frequency harmonics [12]. One method for obtaining the frequency spectra of a discrete array is to use a discrete Fourier transform (DFT) which transforms the input array into an array of complex coefficients [13]. These coefficients specify the amount of each frequency harmonic required.

A. *Transient fault*

When the frequency spectra for different wave forms of data were examined, certain characteristic behavior was apparent. There is more high frequency energy while a secondary arc exists than when it has extinguished as can be seen in fig. 7.

Post arc transient fault waveforms contain a system frequency component usually larger than that of the permanent fault.

It is clear that the behavior of some frequencies is representative of particular stages of the faulted voltage waveform.

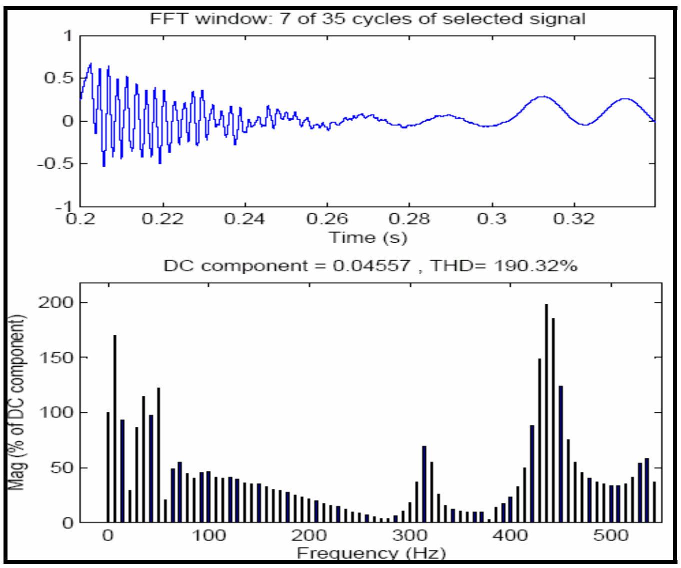

Fig. 7: Secondary arc voltage harmonics content.

C. *Permanent fault waveforms:*

The constant impedance permanent fault waveforms contain only a small system power frequency component. The size of this component depends on the fault impedance, the position of the fault and the coupling between healthy phases. A feature extraction method which measures the energy in seven different frequency bands was used to implement the ASPAR. A discrete 3-phase sequence analyzer blocks are used to observe and calculate the fundamental and harmonic components of the measured signal.

The magnitudes of seven discrete 3-phase sequence analyzer blocks are used to monitor the positive-sequence of the fundamental, DC, second and seventh harmonic voltages (Va, Vb, Vc), the negative-sequence component of the third and fifth harmonics and zero-sequence component of the ninth harmonics.

D. *Method of input vectors selection*

The DFT windows along each case has been thoroughly analyzed. For example the discrete sequences of the same fault case harmonics are given in fig. 8, 9 and 10. The ninth positive sequence peak amplitude during the instance of CB opening contacts is equal to (0.075) pu; while the peak value of ninth negative sequence harmonics is equal to (0.07) pu. But the peak zero sequence value of the ninth harmonics is equal to (0.165) pu. So the ninth zero-sequence discrete harmonics which is given in fig. 10, is the dominant and can be used as a better representative of the fault persistence (***class do-not-reclose***) than the positive or negative sequence which are given in fig. 8 & 9 respectively.

Each frequency domain snapshot of the system derived from any window, can be associated with a particular desired outcome; 'safe to reclose', or 'do not reclose'. Every other frequency domain feature set is combined with its desired outcome to produce a training set suitable for training the ANN. These seven frequency bands provide the core of the feature extraction process.

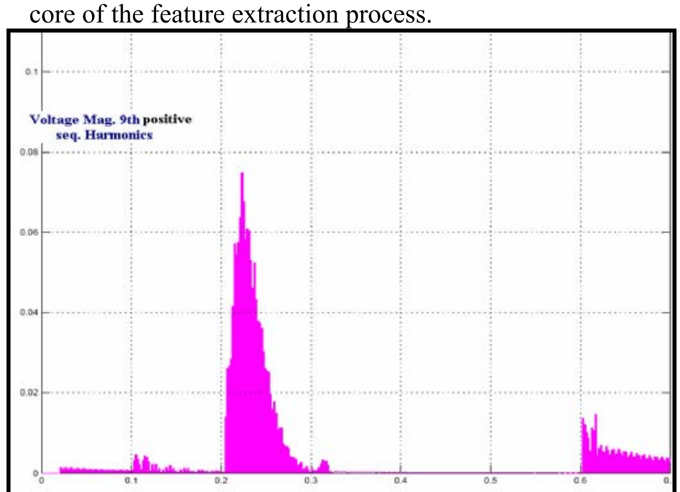

Fig 8: Voltage magnitudes of 9^{th} positive-seq. harmonics.

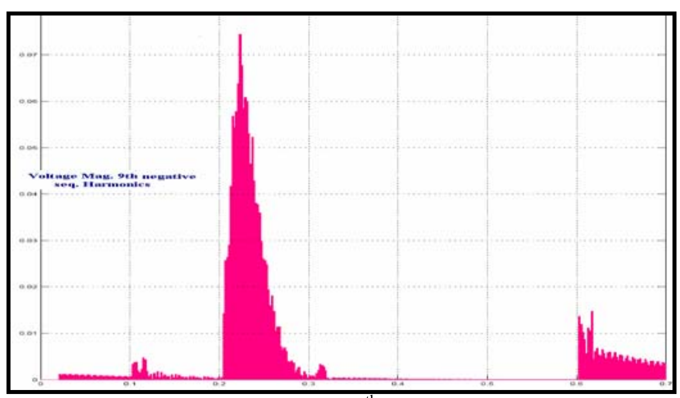

Fig. 9: Voltage magnitudes of 9^{th} negative-seq. harmonics.

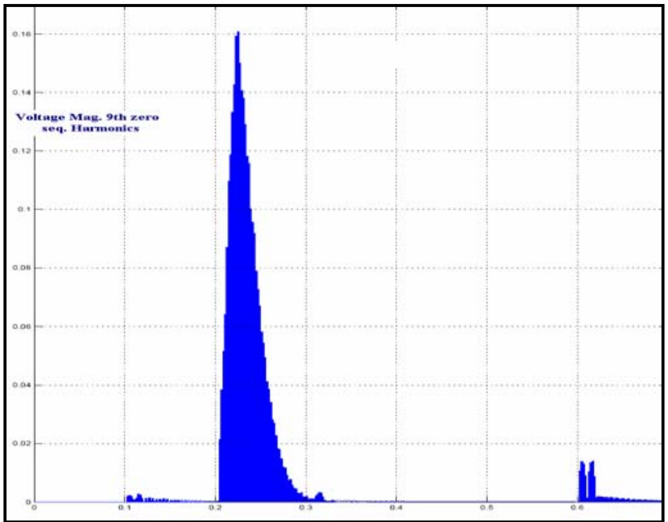

Fig. 10: Voltage magnitudes of 9th zero-sequence harmonics.

V. ARTIFICIAL NEURAL NETWORK TRAINING:

There are many techniques for training a neural network. The training process will adjust the weights associated with neuron inputs [14]. Supervised training works by showing the network a series of matching input and output examples. The network will adjust its weights to accommodate each training example. The training process is complete when the network produces the correct output for every input case. The network's weights are then 'frozen' in their trained states and the network is ready for use. New input data can now be presented to the network, and the network will determine the appropriate output based on its trained connection weights. Although the training process itself can be slow, trained networks are very fast in their operation.

It is this training process that makes neural computing so different from conventional computing [14]. Conventional computer systems have to be explicitly programmed. The problem has to be analyzed in sufficient depth to enable a programmer to write down an explicit, step-by-step series of instructions that the computer should follow to solve the problem. By contrast, neural computing applications are trained to solve the problem and take responsibility for their own internal 'programming' by automatically adjusting the weights.

Following are some important issues related to the application of ANN networks in adaptive single phase A/R relay. They are the summary of experiences gained from the study.

A. Selection of the training data set

The training data set affects the speed of training and the performance of a neural network. Under the assumption that the secondary arcing fault diagnosis problem is a boundary searching process, inconsistence in the training data set, i.e. confusion of data samples around the boundary, could make the neural network very hard to train. If the training convergence limit is set too flexible, the testing accuracy may be lower than the acceptable level. If the training convergence limit is set too strict, the training process may last a very long time and over-training is likely to occur, where the testing accuracy of the training data set is high but it is low for the testing data set. Pre-processing and selection of the training data set could yield good results.

The magnitudes of seven discrete 3-phase sequence analyzer blocks are used while the phases are neglected. The input data selected are the followings:

1. DC positive-sequence component.
2. The positive-sequence of the fundamental (50 Hz).
3. Second positive-sequence (100 Hz).
4. The third negative-sequence component (150 Hz).
5. Fifth negative-sequence harmonics (250 Hz).
6. Seventh harmonic positive-sequence (350 Hz).
7. Zero-sequence component of the ninth harmonics (450 Hz).

B. Over-training

Traditional knowledge from data modeling and recent developments in learning theory clearly indicate that after a critical point, an ANN trained with back-propagation will go on doing better in the training set, but the test set performance will begin to deteriorate. This phenomenon is called over-training [14].

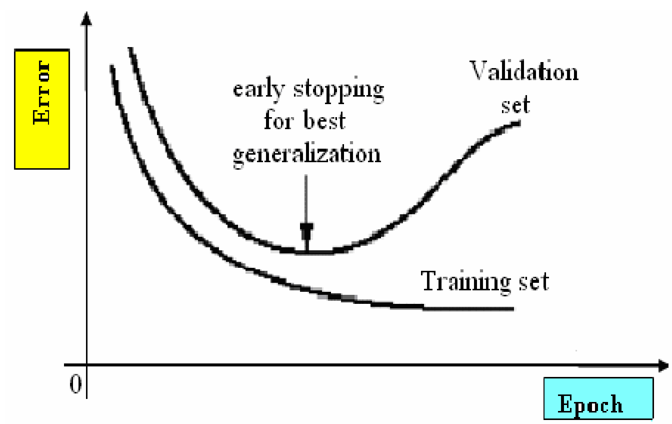

fig. 11: Cross validation or early stopping criterion [14].

One method to solve this problem is stopping the training at the point of maximum generalization (given the present data and topology). This method is called early stopping, or stopping with cross-validation.

It has been experimentally verified that the training error always decreases when the number of iterations is increased (for a sufficiently large network). If we plot the error in a set of data with which the network was not trained (the validation set), indeed the error initially decreases with the number of iterations but eventually starts to increase again as shown in fig. 11. Training therefore should be stopped at the point of the smallest error in the validation set.

To implement this method, the training set should be divided into two sets: the training and the cross-validation sets. The cross-validation set is normally taken as 10 percent of the total training samples. Every so often (i.e., 5 to 10 iterations), the learning machine performance with the present weights is tested against the cross-validation set. Training should be stopped when the error in the cross-validation set starts to increase. This point is the point of maximum generalization.

C. ANN training

In the training of an ANN, two parameters must be properly selected to ensure fast training and convergence. To save training and testing time, which is necessary when the number of data samples is large and the complexity of the network is high, another method was used to evaluate the performance of the network instead of the cross-validation technique [14, 15].

As mentioned before, over-training could be a problem for multiple-source training data set. There are two types of solution for the problem. One is early termination of the training process like setting a flexible training limit, but the side effect of this solution could be a low testing accuracy for both the training data set and the testing data set. The other type is elaborately the select of the data samples of the training data set, making sure they are consistent instead of conflict with each other, which could result in fast training and high testing accuracy.

The number of training patterns (N) required to classify test examples with an error of d is approximately given by:

$$N > \frac{W}{d} \quad \text{--------------------(1)}$$

where W is the number of weights in the network [14]. This equation shows that the number of required training patterns increases linearly with the number of free parameters of the ANN, which is excellent in comparison with other classification methods. A rule of thumb states that $N \approx 10W$, that is, the training set size should be 10 times larger than the number of network weights to accurately classify test data with 90 percent accuracy.

D. Network Size and Generalization

The coupling between the number of required discriminant functions to solve a problem and the number of Processing Elements (PEs) was heuristically established in Chapter 2. From these facts, we could think that the larger the learning machine, the better its performance (provided that there are enough data to train it). The point of scalability shows, however, that larger machines may not learn well, but this is not the most pressing issue [14]. All these arguments pertain to the training data. The fundamental question in any practical application is, how does the learning machine perform on the test-set data? This is the problem of generalization.

ANNs, trained with back propagation, do not control their generalization ability, which can be considered a shortcoming of the technology. Using a cross-validation set to stop the training allows us to maximize generalization for a given network size. However, it does not provide a mechanism for establishing the best network topology for generalization. If we reflect on how the network performs its function, we immediately see that the size of the machine (sometimes called the model complexity) is related to performance: Too few degrees of freedom (weights) affect the network's ability to achieve a good fit to the target function. If the network is too large, however, it will not generalize well, because the fit is too specific to the training-set data (memorization). An intermediate network size is our best choice. Therefore, for good performance, methods of controlling the network complexity become indispensable in the ANN design methodology.

The cross-validation implies that all the data samples are perfect representatives of the problem, but if some of them are not so sure about their desired responses, the method may mislead the optimal ANN topology conclusion [15].

E. Training data

The transient and permanent fault cases locations and vector arrays dimension which are simulated in the model have been summarized and given in Table II, together with the target vectors.

Fault location and type (whether it is transient or permanent fault) at every 5% of the whole TL from Baijie BB to Mosul SG BB (from 0.1% -0.9%), have been examined and simulated in order to achieve the required array of training and test data of ANN.

Close up faults to either BB of Baijie TPS or Mosul SG to about 7% of the TL length, could not be simulated due to the high fault currents and the modeled system in Matlab Simulink become unstable.

Table II: The collected data for training the ANN.

N	FD%	FT	Samples	Trgt	N	FD%	FT	Samples	Trgt
1	10	TF	7x701	1x701	1	10	PF	7x251	1x251
2	15	TF	7x701	1x701	2	15	PF	7x251	1x251
3	20	TF	7x701	1x701	3	20	PF	7x251	1x251
4	25	TF	7x701	1x701	4	25	PF	7x251	1x251
5	30	TF	7x701	1x701	5	30	PF	7x251	1x251
6	35	TF	7x701	1x701	6	35	PF	7x251	1x251
7	40	TF	7x701	1x701	7	40	PF	7x251	1x251
8	45	TF	7x701	1x701	8	45	PF	7x251	1x251
9	50	TF	7x701	1x701	9	50	PF	7x251	1x251
11	55	TF	7x701	1x701	11	55	PF	7x251	1x251
11	60	TF	7x701	1x701	11	60	PF	7x251	1x251
12	65	TF	7x701	1x701	12	65	PF	7x251	1x251
13	70	TF	7x701	1x701	13	70	PF	7x251	1x251
14	75	TF	7x701	1x701	14	75	PF	7x251	1x251
15	80	TF	7x701	1x701	15	80	PF	7x251	1x251
16	85	TF	7x701	1x701	16	85	PF	7x251	1x251
17	90	TF	7x701	1x701	17	90	PF	7x251	1x251
Sum	__	TF	7x11917	1x11917	Sum	__	PF	7x4267	1x4267

From Table II:-

The input p = 7x11917 + 7x4267

p = 7x 16184

The Target t = 1x11917 + 1x 4267

t = 1x 16184

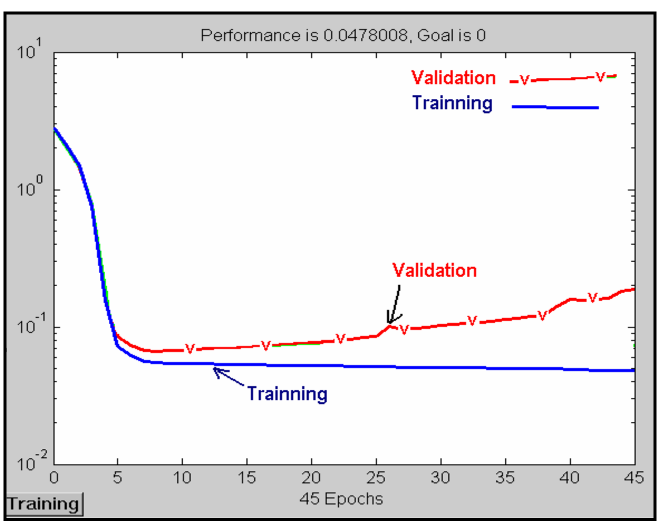

Fig. 12: The training error of the ANN with the validation.

The prepared data divided into two sets; training data (90%) and (10%) for validation. These sets used to train the Multi-layer ANN in order to achieve ASPAR relay performance with a satisfactory decisions. Fig. 12, shows the error of the training data with validation.

A. ANN Topology selection

Even if all the previous steps were taken properly, the ANN topology optimization is still not done. Some topologies may appear to be at the same competitive level. At this moment, engineering judgment is necessary to decide which one is "optimal". The basic consideration is that large number of hidden layer neurons can improve the ANN's diagnostic accuracy to some extent by increasing its complexity, but the improvement may not justify the addition of required resources (memory and processing time).

After examining Table III and applying engineering judgment, 7-21-1 type ANN is selected to be the optimal topology for the adaptive A/R relay shown in fig. 13.

Table III: Performance accuracy (%) of ANN based feature input vector N for data set

N-35-1	N-28-1	N-21-1	N-14-1	Topology
72.25	84.5	91.75	79.25	N = 5
78	90.25	96.25	83.75	N = 7

VI. ADAPTIVE SINGLE PHASE A/R RELAY DESCRIPTION

In the simulation Model only single – phase to Ground fault at different locations along the TL is simulated because it is most popular one (85% of the faults) [3, 4]. Adaptive Single Phase Auto_Reclosing (ASPAR) technique was developed. The processing technique is an ANN which has been trained to recognize secondary arc extinction from the feature extraction of the faulted phase voltage. A feed–forward type ANN paradigms is used with the error back–propagation training algorithm. Levenberg–Marquardt (LM) found to be the best suited algorithm to the problem. Despite that LM training method require large memory, but it is fast in approaching to the recommended decision [13].

The ANN as discussed in chapter two section 3, is a collection of simple processing elements called neurons which are connected together by weights of different strengths. The weights are adjusted by the training procedure upon presentation of examples of data to allow the ANN to classify the tripped phase via a processing stage as a Boolean output of safe to reclose = TRUE or FALSE , 1 or 0, respectively. The ***"safe to Reclose"*** = TRUE condition is represented by out put "1", is used to initiate circuit breaker reclosure. If the secondary arc is not extinguished yet; the tripped phase will not be capable of withstanding the restoration of full system voltage immediately. This means that confidence that "safe to recluse" is TRUE must be incorporated with consideration of the post secondary arc deionization time. Those factors have been incorporated into an ANN output processing scheme with

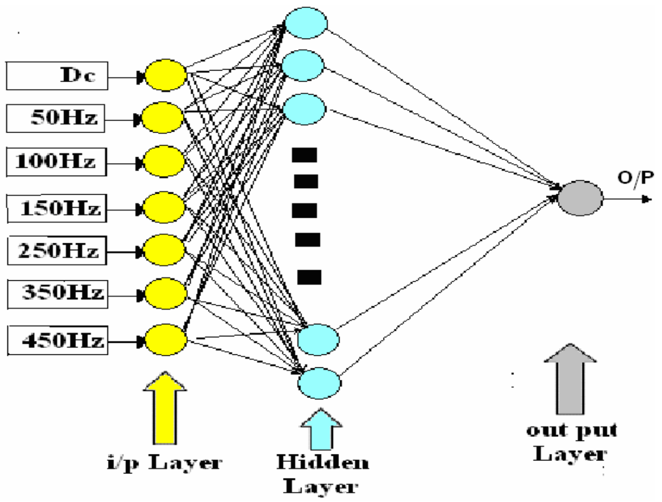

Fig. 13: Topology of the selected ANN of 7x21x1.

in the ASPAR. The situation where confidence in a decision is required is often encountered in power system protection and numbers of techniques such as distance measuring multi–zones and inverse time Over Current (O/C) relays, that is Non Discriminating Protection (NDP) characteristics are commonly employed to address it [4]. The ***"unsafe to reclose"*** = FALSE in the ASPAR will prevent circuit breaker reclosure onto a permanent fault.

However, in the case of conventional Auto_Reclosing scheme, unsuccessful reclosing onto a permanent fault will follow a three phase tripping and lock out operation. Thus ASPAR preventing a second shock and avoiding voltage dip to the system.

V. PROPOSED ASPAR RELAY APPLICATION

The suggested block diagram of adaptive single phase A/R relay application as shown in fig. 14. Three phase analog values secondary voltages from the TL terminal CVTs (R, S and T) will be the inputs of the anti- aliasing filter. All these CVTs have an out put voltage of $110/\sqrt{3}$ volts. An anti-aliasing filter is used to avoid possible errors in reconstructing the input signal, which is carried out after the A/D Sample/Hold section. Any signal sampled at a frequency of N*50 Hz, can exhibit aliasing when reconstructed, if the signal contains harmonic components of order N±1, 2N±1, ….., xN±1. An anti-aliasing filter has to cut off all signal components above the Nyquist rate of N/2, i.e. the cut-off frequency for anti-aliasing filter should be set not higher than (N/2)*50 Hz. In practice however, such a filter cannot

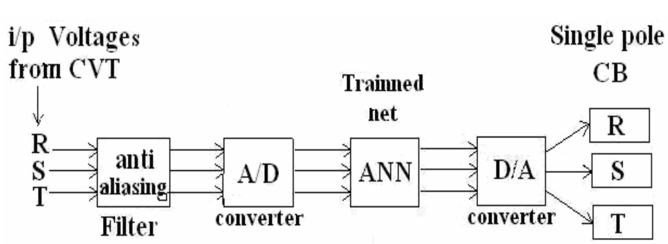

Fig. 14: Proposed ASPAR schematic diagram

remove all out of band frequencies, so the cut-off frequency for the anti-aliasing filter is typically set at about (N/3)*50 Hz. Analog to Digital (A/D) converter sample and hold block will normalize and convert the three phase voltages to digital values suitable to be processed by the ANN block which is consist of the algorithm stored in the processor. Feature extraction and the trained ANN is the core of this digital relay. The output of this block is the decision that have been judged from the input signals to the relevant single phase drive mechanism of the circuit breaker after conversion of this commands from digital to analog values.

CONCLUSION

a) After comparing the study of ANN, two-layer single output ANN based network was identified as the best choice for HV OHTL AR protection. Feed Forward supervised back propagation ANN with 7 neuron in the input layer, 21 neuron in the first hidden layer, 1 neuron in the out put layer identified as the best choice for TL reclosing decision advisor.

b) ANN based Adaptive Single Phase A/R (ASPAR) relay was developed via modification of international standards and addition of special rules. This new adaptive relay successfully advise reclosing commands avoiding reclosures onto permanent fault and recognizes secondary arc extinction, thus issuing right decisions.

c) The ninth zero sequence harmonics have been chosen together with six harmonics sequences to represent the OHTL status (whether it is healthy or not; safe to reclose or do not reclose).

d) Developed ASPAR trained to identify only Single Line to Ground faults both transient and permanent fault types.

e) The modeled circuit which implemented in MATLAB power system block sets, failed to simulate close single phase earth faults to both Bus Bars of Baijie TPS or Mosul SG S/S (up to 6% of TL length), due to the huge fault currents so the simulated system become unstable.

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