NEURAL NETWORK APPLICATIONS IN PROTECTING SERIES COMPENSATED LINES

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ABSTRACT

This paper proposes a technique based on artificial neural networks for fault type classification and faulted phase selection to be used in the protection of series compensated transmission lines. The paper describes in detail the feature extraction, sampling rate, data window length, and training of the desired artificial neural networks (ANNs) . The basic idea of the suggested technique is to use an artificial neural network to identify the fault based on extracting useful features in the desired spectra within a certain frequency range. System simulation and test results are presented and analyzed in this work to indicate the feasibility of using an ANN-based protection scheme in series compensated lines.

Keywords: Protection, Fault Classification, Series Compensated Lines, Artificial Neural Networks.

INTRODUCTION

The use of series capacitor to compensate long transmission lines has become an increasly common practice during the last decade. This is because it:-

a) Increases the carrying capacity of transmission lines.
b) Reduces the losses associated with transmission lines.
c) Improves both the transient and steady state stability of transmission systems.
d) Controls the load flow between parallel circuits.

Series capacitors are either located in the middle of line for less than 50% or at both its ends for compensation greater than that limit. Capacitors are usually protected against over-voltage by means of spark gaps across the terminals and by-pass breakers. Over the last decade, various techniques have been presented to solve the problem of protecting the series compensated lines. Aggarwal et al. [1] proposed a high speed. numerical method based on the directional comparison principle. The basic feature of their proposed method is to use communication channels for extracting information about voltage and current waveforms from both ends of the protected area. The algorithm analyzes this information and determines the location of fault.

Thomas et al. [2] developed an algorithm based on traveling waves technique. The algorithm uses correlation techniques to recognize transient components which departs from the relaying points and returns to it later after a direct reflection from the fault. From the timing of the departure and arrival of these signals at the relaying point, the location of fault can be found.

Abou-El-Ela et al. [3] implemented the phase modified Fourier transform principle suggested by Johns [4] to estimate the impedance of the series compensated lines. He investigated the effect of the subsynchronous resonance phenomena and series capacitor flashover on the performance of distance relay.

Finally, Ghassami et al. [5] modified the technique proposed by Abou-El-Ela et al. [3] and suggested a method for eliminating the source of error in measurement of phase to ground faults due to residual compensation factor.

Neural network applications in electric power engineering can be categorized into four areas: (1) prediction e.g. harmonic evaluation, load forecasting; (2) classification, e.g. transient stability analysis, static/dynamic security assessment; (3)

control and protection, e.g. use of a power system stabilizer, current controller of HVDC system, adaptive autoreclosure; and (4) optimization, e.g. capacitor control, economic dispatching, topological observability.

This paper presents a technique based on artificial neural networks for fault type classification and faulted phase selection to be used in the protection of series compensated transmission lines. The feature extraction and topology of neural networks are discussed in detail.

DIGITAL SIMULATION STUDIES

Highly accurate digital simulations for faulted series compensated lines were used to produce voltage and current waveforms for different types of faults on a line configuration shown in Figure 1. These simulation programs are based on the work of Aggarwel and Johns given in Reference 6. Due to the length and memory requirement, primary system simulation was performed on a main frame computer (DEC VAX 8600) and the resulting waveforms data files were down-line loaded to 80-486 personal computer where the relay simulation is performed.

The faulted feeder for the system under study is a single circuit 500 kV. The earth plane resistance is taken as 100 Ω.m. and the line length is considered to be 300 km. The reactance to resistance for both local and remote sources is 30.0. The zero to positive sequence impedance ratio for both local and remote sources is 1.

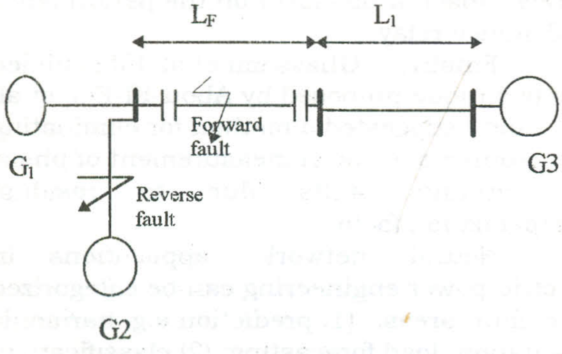

Figure 1 Typical system configurations studied.

All 500 kV lines of lengths $L_1 = L_f = 300$ km; symmetrical short circuit levels for sources: $G_1 = G_3 = 6$GVA, $G_2 = 0.25$ GVA .

Figures 2 and 3 show the voltage and current waveforms under an a-phase to ground fault occurring at 80% of the compensated transmission line. From Figure 2, which indicates the a-phase voltage across the sending end capacitor, it can be noted that when the fault occurs the a-phase spark gap conducts and limits the fault voltage to below the protective level. The curve in Figure 3 expresses the current through the a-phase spark gap. It is shown that once the phase voltage exceeds the preset value, the a-phase spark gap operates. Otherwise, the spark gap does not conduct, and the capacitor is kept in the line all the time.

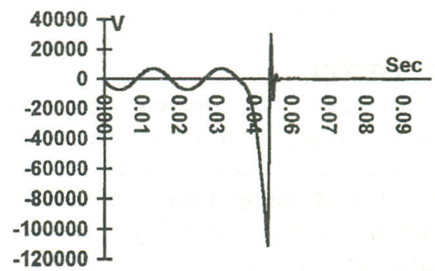

Figure 2 a- phase voltage across sending end capacitor under a-phase to ground fault occurring at 80% of the line

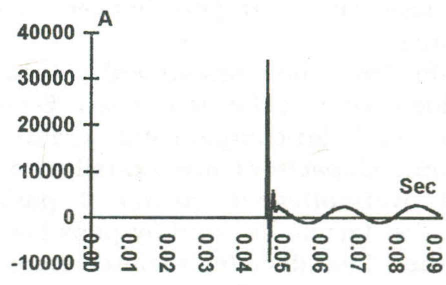

Figure 3 Current through sending end spark gap under a-phase to ground fault occurring at 80% ofthe line.

NEURAL NETWORKS

Neural computation is now one of the most promising technologies in all fields of engineering resulting in the development of a number of artificial neural networks. The basic techniques can be divided into three groups: (i) multilayer perceptron; (ii) selforganization feature mapping developed by Kohonen [7]; (iii) massively interconnected neural networks such as the Hopfield net or the Boltzman machine [7].

The first type has found applications in wide variety of areas. The most popular learning algorithm for adjusting the weights for a multilayer neural network is the back-propagation (BP) procedure. It is based on a steepest-descent approach to minimize the prediction error with respect to connection weights in the network.

The net used in BP procedure is feedforward neural net (FNN). It contains an input layer, an output layer and possibly many hidden layers. Each layer can have one or many processing nodes (neurons). The net input to each neuron in each layer is:

$$I_i = \sum_{j=1}^{n} w_{ij} x_j \qquad (1)$$

where w_{ij} is a set of weighted links and x_j is a set of inputs may come from other neurons or from outside sources. Sum of all weighted inputs represents the node activation. The node output is determined by an output function, which represents this activation. Frequently the so called sigmoid output function is used;

$$f(I) = \frac{1}{1 - e^{-I}} \qquad (2)$$

with derivative:

$$f'(I)=f(I)(1-f(1)) \qquad (3)$$

The node output travels along the link, either to other neurons or to the output of the system. The error in the output layer is the difference between the desired output and actual output:

$$E_j^{output} = y_j^{desired} - y_j^{actual} \qquad (4)$$

The error in the middle layer is backpropagated from output layer and multiplied by the derivative of the middle-layer neuron's activity in forward pass:

$$E_i^{middle} = \frac{df(I_i^{middle})}{dI} \sum_{j=1}^{n} w_{ij} E_j^{output} \qquad (5)$$

The error E and output from previous layer's neuron (incoming signal) are used to adjust the weight changes using the generalized delta rule given by:

$$\Delta W_{ij} = \beta\ E\ f(I) + \alpha\ \Delta W_{ij}^{previous} \qquad (6)$$

$(0.0 < \beta < 1.0)$ & $(0.0 < \alpha < 1.0)$

where, α is the momentum constant and β is the learning constant.

BP algorithm is described in detail in reference[7]. The feedforward neural net used by this algorithm is shown in Figure 4.

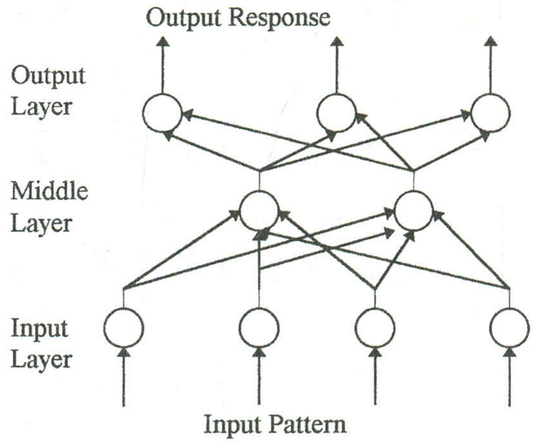

Figure 4 Feedforward neural network

THE STRUCTURE OF ANN

We used in this study the same structure of ANN suggested by Dalstein and Kulicke in Reference 8 Figure 5 shows the structure of this network. The input neurons receive the samples of the normalized currents and voltages at a rate of 1 khz. Five Consecutive sample points of current and voltage of each line are used as inputs. Therefore 30 inputs nodes build up input layer. It also consists of two hidden layers and an output layer with 11 nodes. Each output is responsible for one fault type, except the first node that signals the normal state. Therefore any time of this 11 outputs is mapped to a value of 1 and all other nodes are mapped to a value of 0.

TRAINING AND RESULTS

The program used for generating voltage and current samples at relay location is based on the work of Aggarwal and Johns [6]. The data extracted from this program is used to train and test the ANN suggested by Dastein and Kulicke [8]. Data patterns for different fault types used in the training the ANN extracted for fault locations at 50% of the compensated line, 100% of the compensated line and 20% of the uncompensated line in reverse direction as shown in Figure 1

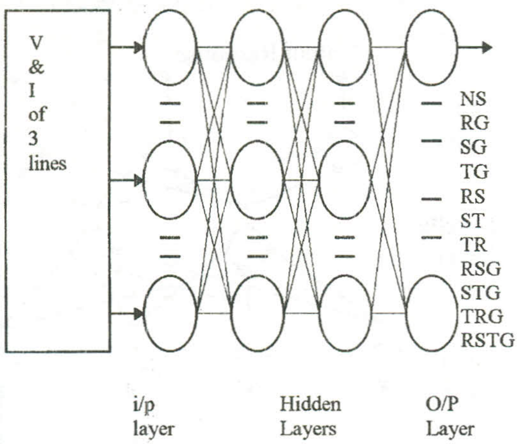

Figure 5 Fault type classification net.

Two cases have been studied to train and test the ANN. First voltage and current patterns are used without filtering. Second a band-pass digital filter is used to extract the useful features of the patterns.

Training and testing without filtering

Figure 6 shows voltage and current spectrums at relay locations for three line to ground fault at 50% of the compensated line. Five equally spaced samples from each pattern are extracted and Table1 is formulated. The first column of this table represents the values of phase voltages and line currents at fault instant. Other four columns represent the values of these patterns at other consecutive samples. Similar tables can be formulated for other fault types at other fault locations.

It has been found , that a net with 30 inputs 20 nodes in the first hidden layer, 15 nodes in the second hidden layer and 11 outputs (30-20-15-11) is capable to minimize the error E to a final value of 0.01. We used the Backpropagation Training Algorithm with dynamic learning rate. Therefore, the possibility of weight changing decrease cycle by cycle until training is stopped. This learning strategy converges quickly. In Figure 7 we demonstrate the learning error E over 317 iterations. One can see that the learning error decreases in 317 iterations to 0.01.

The ANN is tested by two data sets. First the data set used for training the network is used another time for testing. Table 2 shows that all nodes response correctly for this data set. The second data set used for testing the net is extracted from 20% and 80% fault locations. The output of RSTG node does not response correctly for both fault locations as shown in Table 3. This means the feature of the RSTG patterns is not recognized by network for fault locations other than used in the training.

Filtering the input data by band-pass filter

The frequency response of the filter used in this study is shown in Figure 8. It has 4 kHz sampling rate and 6 msec data window length. This filter is used to extract the high frequency harmonics and DC offset from the voltage and current patterns. Figure 9 demonstrates the filtered patterns for three line to ground fault at 50% of the compensated line. One can see that the filter is capable to remove unwanted noise from the signals.

Table 4 is formulated by decimating down in time the filtered patterns to 1Khz and five consecutive samples after 6msec (the length of the filter) from the instant of the fault are extracted from the voltage and current patterns. This table represents the input pattern to ANN for three line to ground fault at 50% of the compensated line. Similar tables can be formulated for other fault types at other fault locations.

The structure of ANN (30-20-15-11) used in the first case has been used here for a second time. The network is capable to minimize the error E to a final value of 0.01. In Figure 10 we demonstrate the learning error E over 584 iterations. We can see that the learning error decreases in 584 iterations to 0.01.

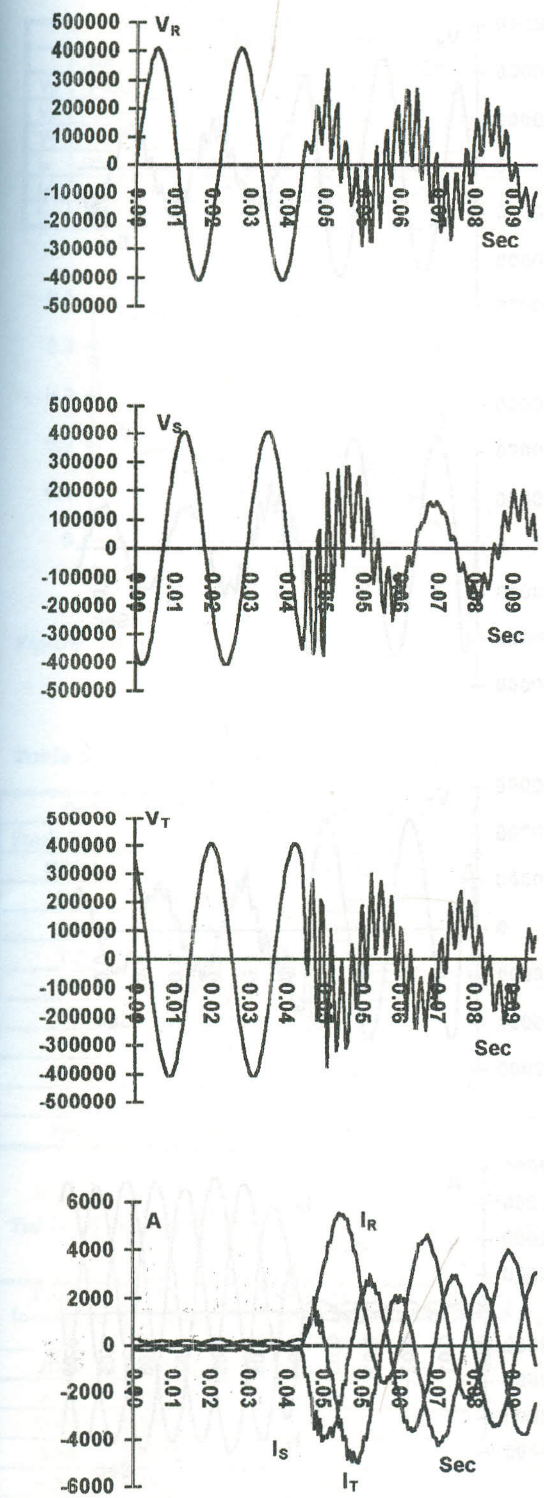

Figure 6 Voltage and current patterns observed by sending end relay for 3-line to ground fault at 50% of the compensated line.

Table 1 Input to ANN for three line to ground fault at 50% of the compensated line.

	Sample's Number				
	1st	2nd	3rd	4th	5th
V_R	1737.2	54999	109190	118200	229880
V_S	-354150	184680	-369480	22868	-375560
V_T	352390	-254130	276689	-149710	184380
I_R	275.38	552.87	1076.9	2105.39	2944.7
I_S	-129.77	-589.94	-2075.8	-3051.6	-4084.1
I_T	-154.56	2.876	954.65	888.38	1087.7

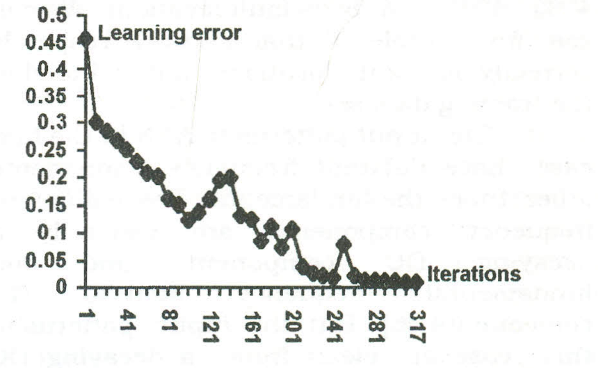

Figure 7 The learning error for training without filtering the input data.

Table 2 Testing the ANN with the training data

Output of ANN for the training fault locations			
Fault Types	**50%**	**100%**	**20% in Rev.**
RSTG	0.994	0.997	0.995
RG	0.971	0.971	0.981
SG	0.98	0.978	0.978
TG	0.992	0.992	0.991
RS	0.959	0.959	0.959
ST	0.9895	0.985	0.984
TR	0.9654	0.965	0.96
RSG	0.964	0.964	0.98
STG	0.991	0.973	0.993
TRG	0.986	0.986	0.984

Table 3 Testing the ANN with data extracted from 20% and 80% fault location patterns

Fault locations	Fault types	Output of fault type node	Output of other nodes
20%	RSTG	0	0 except TRG = 0.9869
20%	RG	0.9572	0
20%	RS	0.9592	0
80%	RSTG	0	0 except RG = 0.9359
80%	RG	0.9717	0
80%	RS	0.9592	0

It is noted the number of iterations in this case is different from the first. This is because the initial weight values and the training set used here to train the network are different from those of the first case.

Two tests have been done to check the response of the network for the input data patterns. First the training data set have been used and we can see from Table 5 that all nodes respond correctely for this set. The second data set is extracted from 20%, 40%, 60% and 80% fault locations. We can see from Table 6 that network responds correctly for fault locations not included in the training data set.

The input patterns to ANN in the first case have different frequency components other than the fundamental. These different frequency components are, generally, a decaying DC component and non fundamental frequency (non-50 Hz) components [6]. But the input patterns in this case are clean from a decaying DC component and is much less corrupted by nonfundamental components as shown in Figure 9 It is evident that the band-pass filter with characteristic shown in Fig. 8 is capable to compress the range of the feature signals and improves the performance of ANN.

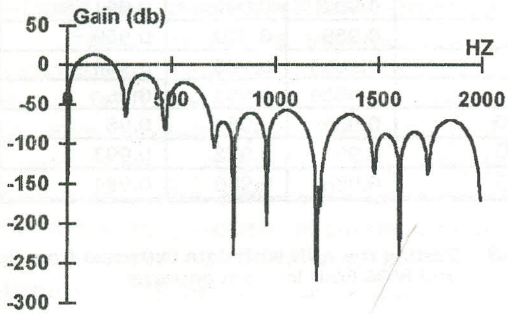

Figure 8 Frequency response of the digital filter.

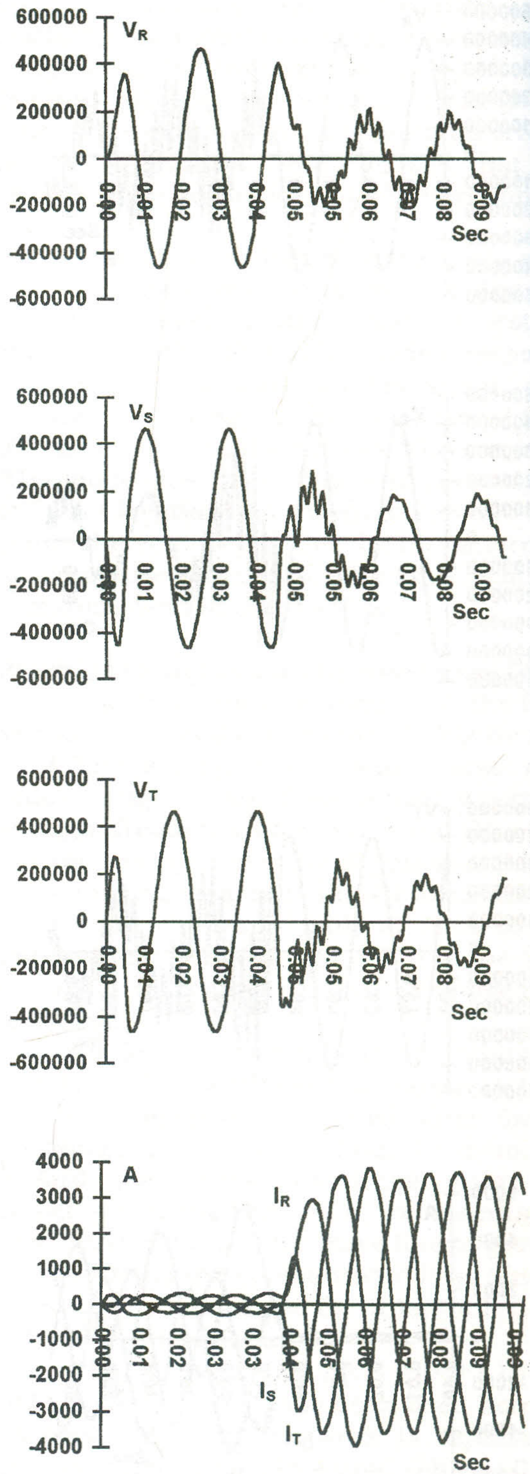

Figure 9 Filtered patterns observed by sending end relay for 3-line to ground fault at 50% of the compensated line

Table 4 Filtered input to ANN for three line to ground fault at 50% of the compensated line.

	Sample's Number				
	1st	2nd	3rd	4th	5th
V_R	146005	36286.1	-34163	-168243	-139674
V_S	-26842	233836	149452	270211	110443
V_T	-75941	-237413	-85813	-155451	-27835
I_R	2581.96	2938.9	2894.6	2498.4	1485.5
I_S	-2552.8	-1443.4	-354.16	817.883	1947.36
I_T	-111.74	-1712.6	-2832.8	-3549.5	-3445.3

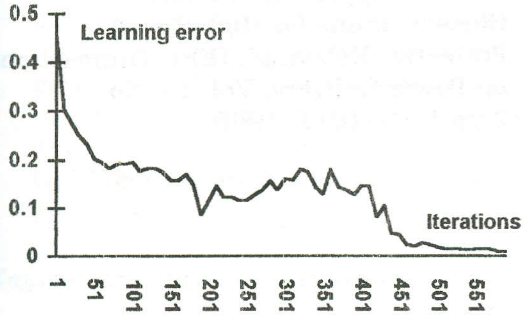

Figure 10 The Learning error for training with filtering the input data.

Table 5 Testing the ANN with the training filtered data.

Output of ANN for the training fault locations			
Fault Types	50%	100%	20% in Rev.
RSTG	0.9952	0.9952	0.9851
RG	0.9949	0.9949	0.9949
SG	0.9942	0.989	0.9942
TG	0.9965	0.9965	0.9965
RS	0.9955	0.9955	0.9956
ST	0.9858	0.9858	0.9858
TR	0.9877	0.9194	0.9937
RSG	0.9932	0.9932	0.9942
STG	0.9498	0.9498	0.9971
TRG	0.9984	0.9748	0.9993

Table 6 Testing the ANN with filtered data extracted from 20%, 40%, 60% and 80% fault location patterns.

Fault locations	Fault types	Output of fault type node	Output of other nodes
20%	RSTG	0.9901	0
20%	RG	0.9851	0
20%	RS	0.9817	0
80%	RSTG	0.9896	0
80%	RG	0.9851	0
80%	RS	0.9817	0
40%	RSG	0.993	0
60%	RSG	0.9545	0

It is possible to increase the data window length more than five samples and include the different frequency components in the fault signals. This will improve the performance of the ANN in the first case but slow the decision of tripping signal made by the relay. But, according the power system protection requirements, the faster the trip signal needed, the shorter the data window required. Therefore, an increasing data window length of the ANN to include different frequency components in the faulted signals is not suitable for power system protection.

CONCLUSIONS

This paper proposes a technique based on ANN's for fault identification to be used in protection of series compensated lines. Two cases have been studied to train and test the ANN. First the input patterns are extracted from the corrupted voltage and current waveforms. In this case the network responds incorrectly for patterns not included in the training data set. In the second case a band-pass digital filter is used to compress the frequency range of the input patterns to the network. This will improve the performance of the network as shown by the results in table-6 but delays by 6 msec the trip signal made by the relay.

APPENDIX

The line self and mutual impedances are given below:-

$Z_1 = 0.0345 + J\,0.309 \quad \Omega/km$

$Z_0 = 0.2979 + J\,0.99894 \quad \Omega/km$

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