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DETECTION AND IDENTIFICATION OF FAULTS IN UNDERGROUND CABLE USING ARTIFICIAL NEURAL NETWORK

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Abstract: This paper presents an Artificial Neural Network (ANN) simulated model of fault detection and identification in an underground cable network. To be precise, a two-step sectionalized process is carried out in a phased manner. Step one is initiated by the modelling of transmission system using MATLAB-SIMULINK followed by the creation of faults in the system network. Secondly the Fourier analyzed fault parameters obtained from the Simulink model is fed to the training set of ANN. Identifying the fault type plays a vital role as the sudden outcome of different fault types implicate the stability, reliability and other serious post fault effects which is to be suppressed before identifying the location and method of isolation.

Index Terms **– Underground cable, Simulink, ANN, Training, Fault types.**

Nomenclature -

V_R =	**Fault voltage of phase R**	**I_R = Fault current of phase R**	
V_Y =	**Fault voltage of phase Y**	**I_Y = Fault current of phase Y**	
V_B =	**Fault voltage of phase B**	**I_B = Fault current of phase B**	

I. INTRODUCTION

The main aim of this paper work is to detect and identify the type of fault in underground cable. In urban and densely populated areas considering safety, use of underground cables are preferred in the recent decades comparing to overhead lines though the latter has less complications during fault diagnosis. Since cables are buried under the ground using ducts and channels, whenever there is a fault in the cable, it becomes difficult to locate, identify and repair as the cables are not readily accessible for inspection. Not an exception, the underground cables are subjected to wide variety of faults due to bulk power handling, insulation failure, wear and tear, rodents, ageing etc. The ever increasing power handling load capacity increases the complexity of the system network which in turn poises a big task for the stability of transient and steady state network of the system. Hence a proper method of fault detection and identification is necessary before the diagnosis of the fault.

Though numerous faults detecting and identifying techniques were proposed in the literature, each method has its own boundary. With the help of developing technology, it takes less time to detect, locate and isolate the faults. However, every method of approach has certain limitations which makes no single method to be ever superior. Many methods of different types are suitable for specific type of different faults. The ANN method imitates the biological capability of solving linear and non-linear systems. Thus, it can be implemented for the complete protection of power system in the field of fault analysis, detection, identification, location, diagnosis and many such research publications were widely augmented in this area. This makes the ANN method an efficient and safe localization of faults without damaging the entire network.

II. SYSTEM MODEL

A. UNDERGROUND CABLE SIMULINK MODEL

Modelling of overhead lines and underground cables are primarily based on their length and rated voltage. Two types of modelling approximation are used in general: Lumped parameter model and Distributed parameter model. Here the underground cable is modelled using the distributed parameter line in Simulink and is shown in Fig.1. A 1.1kV 10km cable with following parameters are used for the simulation.

R=0.0127 Ω/km, L= 0.9337 mH/km, C= 12.741 μF/km.

The fault distance is assumed to be at a distance 5km from source or midpoint of the line. The fundamental component of the voltages and currents at various fault points are obtained using Fourier blocks at the sending, receiving and fault points respectively. The fundamental values of voltages and currents obtained for each fault case is tabulated and used for the detection of fault type.

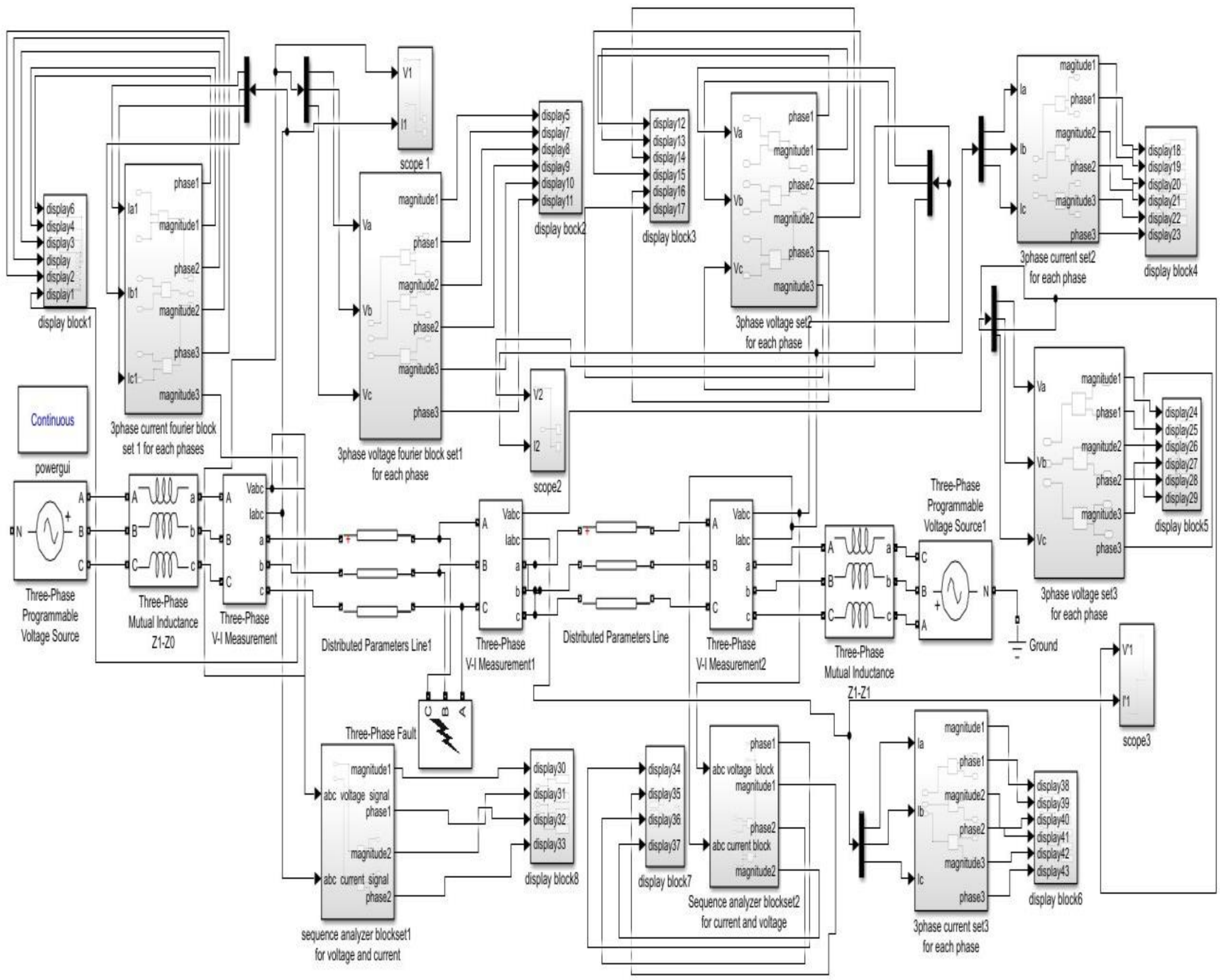

Fig.1. Underground cable Simulink model

B. INCEPTION OF VARIOUS FAULTS

Fault detection is analysed by fixing the faulty data target location using fault block in the simulink. The simulated waveforms of the fault voltages and fault currents for different fault types were analysed for comparison. Single line to ground fault, double line to ground faults, LL faults and LLLG faults are incepted to the simulink model for obtaining a large set of data so that ANN model used in the next level can be properly trained. The waveforms of LG fault with phase Y to ground and LLG fault with phase R and Y to ground has been shown in Fig.2 and Fig.3 respectively. The fundamental values of the fault voltages and currents for various faults at different time instants are tabulated for the purpose of training.

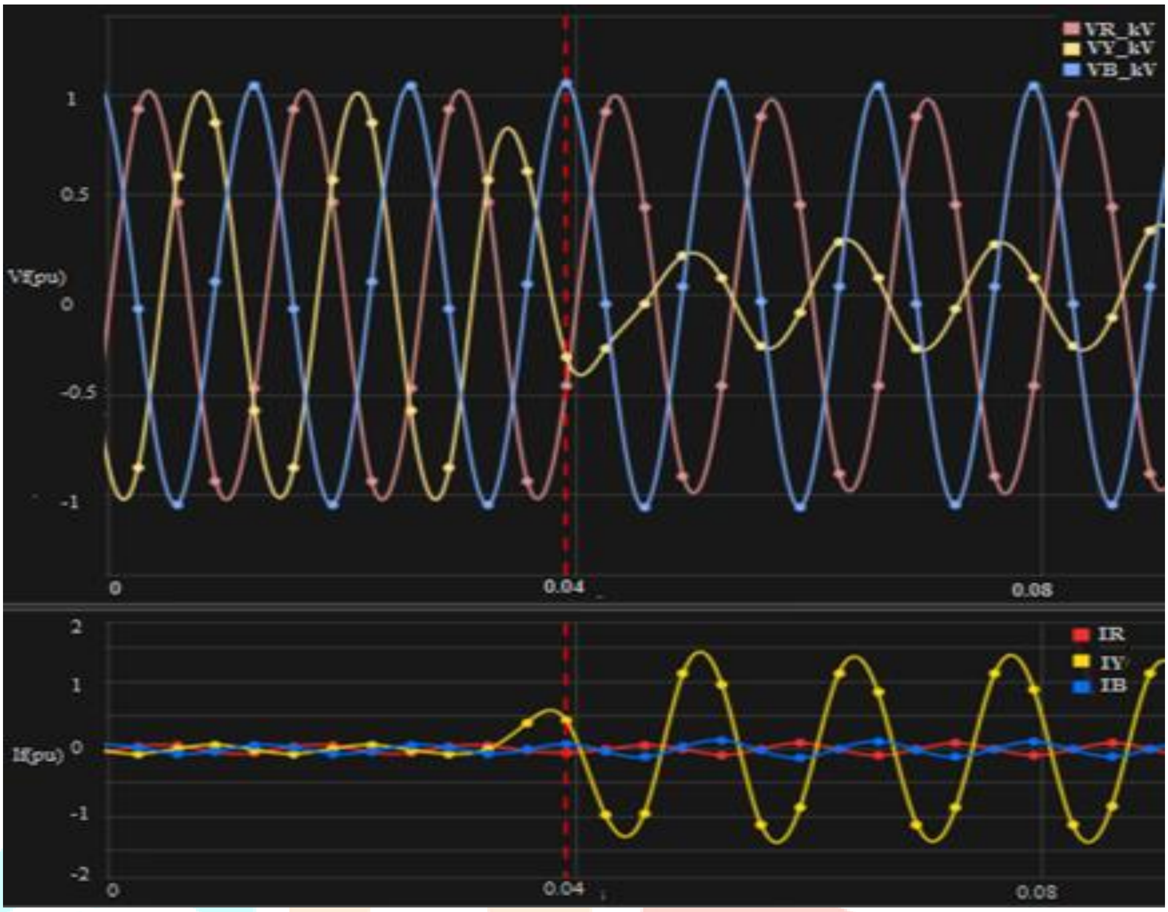

Fig.2. Fault voltage and current waveforms of LG fault with phase Y to ground

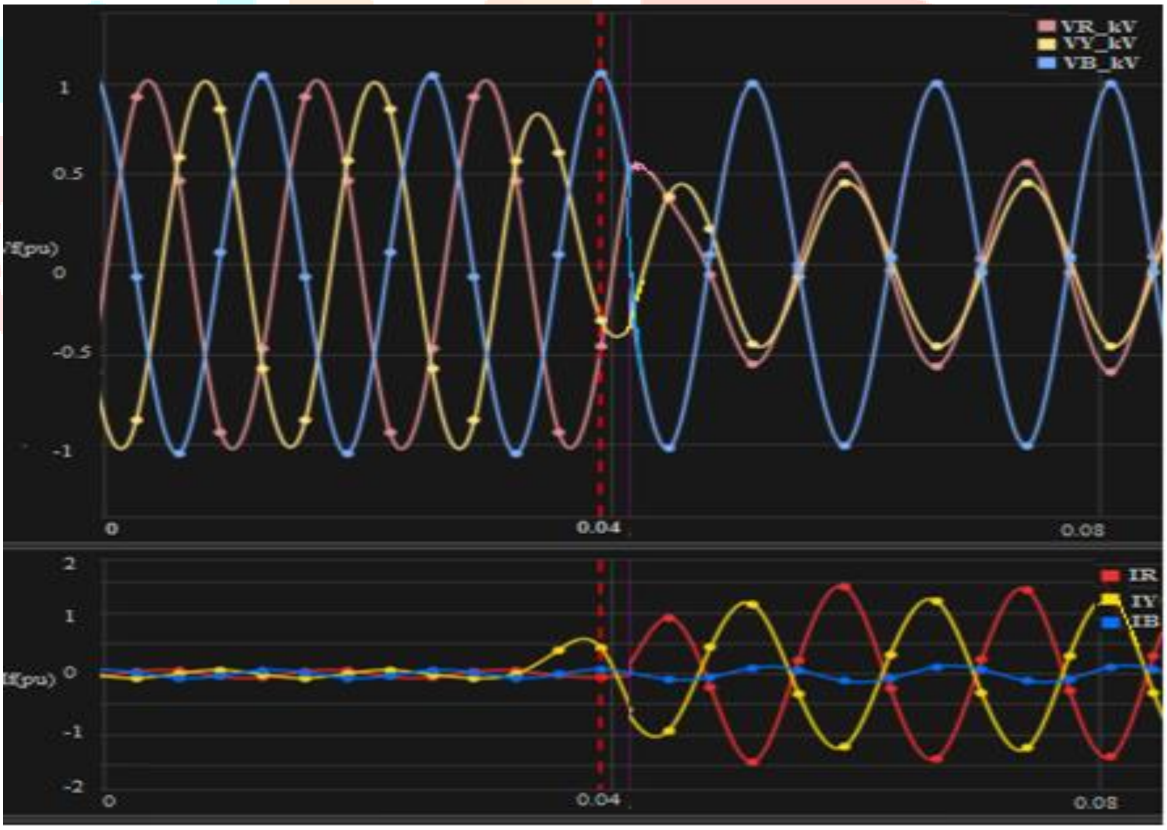

Fig.3. Fault voltage and current waveforms of LLG fault with phase R and Y to ground

C. SIMULATION RESULTS

By fixing the simulation run time at 0.1 second, the Fourier block in the simulink model provides the fundamental values of phase voltage and phase current for each type of fault. The results from this block are tabulated and the training data set are formed using this for the succession of next step.

III. FAULT IDENTIFICATION USING ANN

A. ARTIFICIAL NEURAL NETWORK

Research based on ANN shows more interesting output in the protection of power system with fault analysis. ANN which works on the learning ability of human from its surroundings, adapting itself to it and responding accordingly is utilized for the protection purpose by training the network with past records, measurements, available data, and observations. In this paper, the parameter variations obtained during the fault detection are fed as computational models in the ANN which represents a system of interconnected neurons whose computational values are obtained from the inputs.

B. TRAINING OF ANN

Initially, the Artificial Neural Network is to be trained by using supervised training. In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which controls the network. This process occurs over and over as the weights are continually tweaked. The set of data which enables the training is called the "training set."

The training data set is obtained from the Fourier blocks of the simulink model. Using this data set, the Neural network develops a relationship among the given data and show results for any desired input as per its unique ability of decision making. A set of values with fault voltages and currents obtained from the simulink model at 0.06s is shown in Table 1.

Table 1. Training data set for ANN

Case	**V_R**	**V_Y**	**V_B**	**I_R**	**I_Y**	**I_B**	**Fault type**
1	0.6924	0.6918	0.6934	1.901	1.9	1.9	No fault
2	0.000121	0.3428	-0.758	3.921	1.902	1.9	LG(RG)
3	0.5009	0.5008	0.2025	0.1225	-0.5184	-0.1134	LG(YG)
4	0.3823	0.7638	0.0001	1.9	1.9	5.306	LG(BG)
5	-0.3127	-0.112	0.7524	-1.004	1.092	0.0041	LLG(RYG)
6	0.0001	0.4923	0.0001	3.763	1.9	6.123	LLG(RBG)
7	-0.4998	0.0001	0.0001	1.9	5.342	3.412	LLG(YBG)
8	0.2891	0.289	0.6732	3.109	3.491	1.9	LL(RY)
9	0.6953	0.2823	0.2822	-1.9	3.512	3.5	LL(YB)
1 0	-0.2834	0.685	0.2786	3.821	1.9	-3.91	LL(RB)
1 1	6.70E-05	5.90E-05	6.50E-05	3.80E+00	3.28E+00	3.64E+00	LLL(RYB)
12	6.70E-05	5.90E-05	6.50E-05	3.80E+00	3.28E+00	3.64E+00	LLLG(RYBG)

Similar training sets are developed at different timing instants (0.05s, 0.055s etc.) for an effective training of the ANN. The ANN is trained with the help of four variables i.e., phase R, Y, B and G(ground) either being in high state or low state. For instance, a LG fault between Y and G, the ANN is trained such that Y and G are set at high (1) state and R and B are at low (0) state. In case of LLG fault between R, Y and G, the ANN is trained such that R, Y and G are at high (1) state and B at low (0) state.

C. ANN OUTPUT

After the training of Neural network, it is to be tested and validated for known faults. For this, the values of fault voltages and currents obtained from the Simulink model were fed as input to the ANN block. The symmetrical simulated system with three phases is represented by Red, Yellow, and Blue lines respectively and that of ground is represented by a Green line. A high (1) state in a line indicates that the phase corresponding to that line is under fault. In Fig. 4, Yellow and Green lines are near logic 1 whereas rest are at logic 0. This describes a LG fault between phase Y and ground. Similarly, Fig.5 describes a LL fault between R phase and Y phase. This logic can be further extended for any type of fault occurring at any time.

Fig. 4. Fault detection for LG(YG) fault using ANN

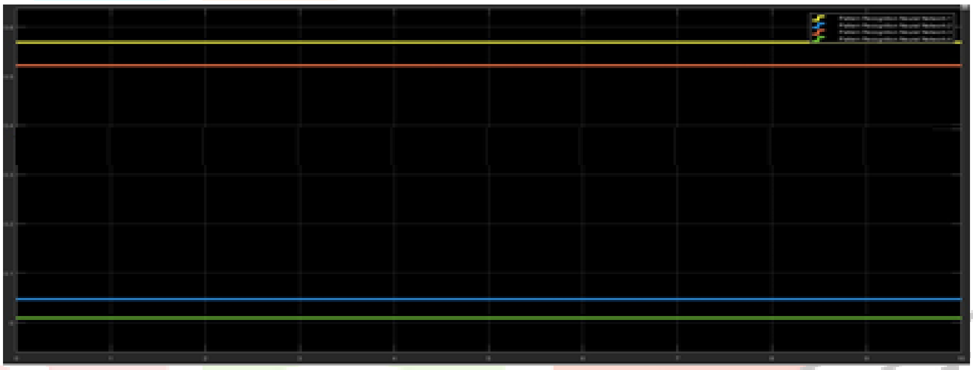

Fig. 5. Fault detection for LL(RY) fault using ANN

IV. CONCLUSION

This paper proposed a method to detect and identify different faults in an underground cable with the help of Simulink and ANN. Using this method an underground cable of any determined length or its prototype can be modelled in Simulink with the constraints of distributed parameter line and the variation of its performance parameters can be assessed with the injection of a known or incipient faults in the modelled network. The effective tracing of parameter variations can be achieved by inducting Fourier technique in the simulink. The fundamental values of fault voltages and fault currents are then obtained and tabulated which act as the training set for the ANN model. Once the network is modelled, the ANN model interconnected with the Simulink represents a real time underground cable network. So, if any fault occurs in the cable, it can be easily detected and identified using the proposed method of ANN model. Hence, the proposed method has a short recovery period during the detection and identification of various faults in underground cables.

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