iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 5 **Issue:** X **Month of publication:** October 2017

DOI: http://doi.org/10.22214/ijraset.2017.10174

Artificial Neural Network Based Fault Location Estimation of Double Circuit Transmission Line

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Abstract: An accurate fault location estimation algorithm based on application of artificial neural networks (ANN) for the protection of double circuit transmission lines is presented. The proposed Artificial Neural Network (ANN) protection scheme uses fundamental components of three phase voltages and current signals of both the circuits to learn the hidden relationship in the input patterns. This method is adaptive to the variation of fault resistance, fault inception angle and fault location. The Simulation results show that all types of shunt faults can be correctly locatedunder varying system conditions. Large numbers of fault simulations using MATLAB/Simulink software has proved the accuracy and effectiveness of the proposed algorithm.
Keywords: Fault location (FL); Double circuit transmission line; artificial neural networks (ANN).

I. INTRODUCTION

Double circuit transmission lines are being most widely used because it has increased the power transmission capability and reliability of the power system. Distance relays used for protection of transmission lines have problems of under-reach, over-reach and mal-operation due to high impedance faults. Further this problem of distance relay is compounded when the distance relays are used for protection of double circuit transmission lines due to mutual coupling effect between the parallel lines. All possible types of faults on double circuit transmission line should be detected, classified and located correctly. The fault location of double circuit lines becomes more difficult and complex than a single circuit line due to the effect of mutual coupling among the circuits. When the fault location algorithm developed for single circuit lines is directly used for double circuit lines, which is often the case in practice, the fault location estimation accuracy can’t be guaranteed because of the mutual coupling effect. Therefore a dedicated fault location algorithm has to be developed for the double circuit transmission lines.

In previous years, various fault location algorithms on double circuit transmission lines have been developed [1-15]. Phase selection algorithm based on superimposed components for protection of double circuit transmission line was proposed in [1] and [2]. A faulted-phase selector based on superimposed sequence components combined with correlation theory was presented in [3]. A fault classifier based on fault-generated high-frequency noise and artificial neural networks was proposed in [4]. In [5] the wavelet transform was used to extract the characteristics of the transient signals to construct the phase selector. In [6] Wavelet fuzzy combined approach for fault classification of a series-compensated transmission linewas presented. The fault classification and faulted-phase selection based on the Initial current travelling wave was reported in [7]. In [8] and [9] the algorithm employs the faulted circuit and healthy circuit of two-parallel line as fault location model and fault type is identified using computer program based on Newton Raphson method.

There are many other papers which combine the artificial intelligent methods for fault classification, faulted-phase selection and fault distance location [10]–[16]. In [11] Application of neural network for faulty phase selection and distance location for single circuit transmission lines has been reported.Fault classification for double-circuits using self organization mapping neural network was presented in [12], however it does not locate the faults. In [13] the researcher has developed a complete protection scheme for a single circuit transmission line. The work presented in [14] deals with the compensation of fault resistance using ANN, it does not classify the faults. A single line to ground fault location method employing wavelet fuzzy neural network to use post-fault transient and steady-state measurements in the distribution lines of an industrial system is proposed in [15], it does not classify the faults. An application of artificial neural network for phase to phase fault classification and location in a double end fed double circuit transmission line using only one terminal data considering the effects of varying fault location, fault inception angle and remote source infeed has been proposed in [16]. This algorithm uses the fundamental components of three line voltages and the six line currents of the two parallel lines at one end only.

This paper proposes an enhanced algorithm to determine the fault location on double-circuit transmission line for all possible types of shunt fault using only one terminal data considering the effects of varying fault location, fault inception angle and fault resistance. The proposed algorithm uses fundamental components of three phase voltages and current signals of both the circuits to

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue X, October 2017- Available at www.ijraset.com

learn the hidden relationship in the input patterns.Its effectiveness has been tested on a double-circuit transmission system through various simulations using MATLAB. Simulation results of the proposed algorithm have shown its accuracy of the fault location in all cases considered.

II. POWER SYSTEM NETWORK SIMULATION

The power system network studied is composed of 220KV, 50 Hz, 100km double-circuit transmission lines, connected to a source at each end, as shown in Fig. 1. All components of the power system network are modeled by the MATLAB ® Simulink & SimPowerSystem toolbox. The transmission line is simulated using distributed parameter line model. The short circuit capacity of the equivalent Thevenin sources on two sides of the line is considered to be 1.25 GVA. Xs/Rs ratio of each source is 10. A load of 80 MW and 50 MVAR is connected at the receiving end side of transmission line. The double circuit transmission line parameters are shown in Table-1.

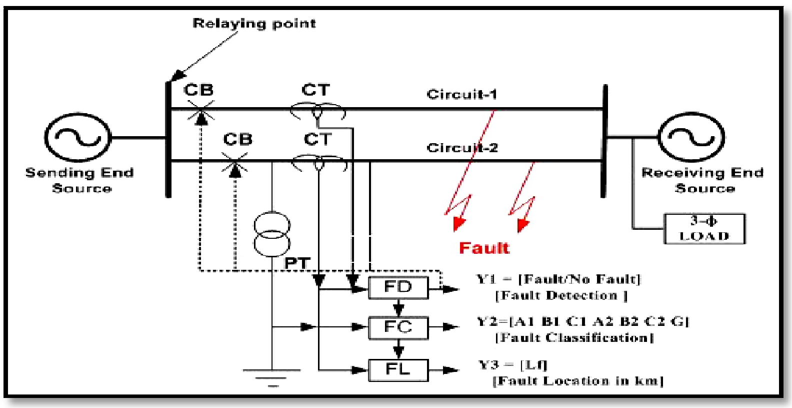

Figure 1: Single line diagram of power system model under study

Components	Parameters	
Transmission line	Length (km)	100
	Voltage (kV)	220
	Positive sequence impedance (Ω/km)	0.0181 + j0.292
	Zero sequence impedance (Ω/km)	0.2188 + j1.031
	Zero sequence mutual impedance (Ω/km)	0.20052 + j0.6535
	Positive sequence capacitance (nF/km)	12.571
	Zero sequence capacitance (nF/km)	7.8555
	Zero sequence mutual capacitance (nF/km)	-2.0444

Table 1: Double circuit transmission line parameters

III. ANN BASED FAULT DISTANCE LOCATOR

The basic procedure used to implement a neural network for the fault location algorithm in double circuit transmission line is described below.

A. Selecting the right architecture:

The main factor in determining the right size and structure for the neural network is the number of inputs and outputs that it must have. The inputs to distance relay are mainly the voltages and currents, therefore the network inputs chosen here are the magnitudes of the fundamental components (50 Hz) of three-phase voltages and six currents measured at the relay location at one end of the line. Thus the network inputs for fault detector, fault classifier and fault locator are total nine as given in (1). Five post-fault samples of fundamental components of three-phase voltage and phase current signals are extracted to form the input matrix of ANN-based fault locator as given in (2).

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$$X = [\, V_a,\ V_b,\ V_c,\ I_{a1},\ I_{b1},\ I_{c1},\ I_{a2},\ I_{b2},\ I_{c2}\,] \qquad (1)$$

$$X = \begin{bmatrix} V_a(n) & V_a(n+1) & . & . & . & V_a(n+4) \\ V_b(n) & V_b(n+1) & . & . & . & V_b(n+4) \\ V_c(n) & V_c(n+1) & . & . & . & V_c(n+4) \\ I_{a1}(n) & I_{a1}(n+1) & . & . & . & I_{a1}(n+4) \\ I_{b1}(n) & I_{b1}(n+1) & . & . & . & I_{b1}(n+4) \\ I_{c1}(n) & I_{c1}(n+1) & . & . & . & I_{c1}(n+4) \\ I_{a2}(n) & I_{a2}(n+1) & . & . & . & I_{a2}(n+4) \\ I_{b2}(n) & I_{b2}(n+1) & . & . & . & I_{b2}(n+4) \\ I_{c2}(n) & I_{c2}(n+1) & . & . & . & I_{c2}(n+4) \end{bmatrix} \qquad (2)$$

As the basic task of fault location is to determine the distance to the fault. Therefore fault distance in km with regard to the total length of the line, should be the only output provided by the fault location network. Thus the output Yfor the fault location network is given as in (3).

$$Y = [L_f] \qquad (3)$$

B. Training Dataset Generation

Training dataset of ANN consist of input and corresponding target dataset. To get the input the power system model is simulated at different location, inception angle and resistance in MATLAB. Table 2 gives the various combinations of fault types and parameters for input pattern generation.

Parameters	Set Value
Type of Faults (4)	A_1G, B_1G, C_1G, A_2G, B_2G, C_2G, A_1B_1G, $B_1\,C_1G$, A_1C_1G, A_2B_2G, B_2C_2G, A_2C_2G, A_1B_1, B_1C_1, A_1C_1, A_2B_2, B_2C_2, A_2C_2, $A_1B_1C_1$, $A_2B_2C_2$
Fault Location (11)	1,10,20,30,40,50,60,70,80,90,99
Fault Resistance (4)	1,50,80,120 Ω (for ground fault) & 0 Ω (for phase fault)
Fault Inception Angle (2)	0º & 90º

Table 2: Training Data Pattern Generation

C. Training of Fault Locator

The network for fault locator is trained using "Levenberg Marquard Algorithm". The goal achieved is shown as the minimum number of root mean square error meets after a significant number of iteration. The number of hidden layer neurons and transfer function is chosen based on the "trial and error" method.

1) Training for LG Fault: Here two hidden layer of 24 and 12 neuron in first and second hidden layers respectively and 'tansig' transfer function is used for both hidden layer and 'purelin' transfer function is used for output layer that gives the best performance as shown in Fig. 2. The network of fault locator is multi layered feed forward ANN with 9 neurons in the input layer, 24neuron in first hidden layer, 12 neuron in second hidden layer and 1 neuron in output layer (9-24-12-1) is capable of minimizing the mean square errors (MSE) to a goal of $9.97 * 10^{-07}$ in 1374 epochs as shown in Fig. 3.

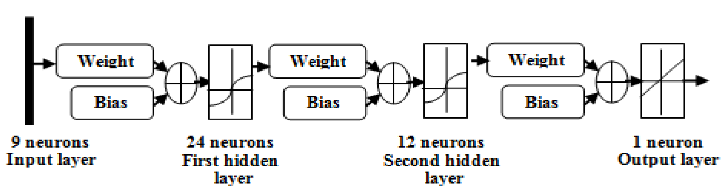

Figure 2: Architecture of ANN Based LG Fault Locator

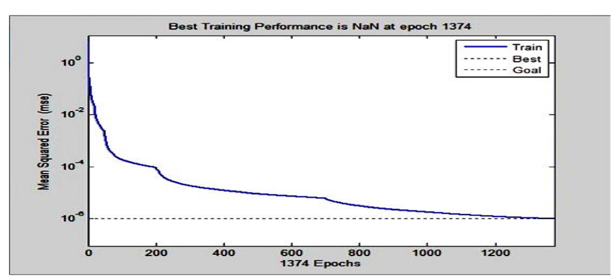

Figure 3: ANN training performance (MSE) for LG Fault Locator

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
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2) Training for LLG Fault: Here two hidden layer of 24 and 12 neuron in first and second hidden layers respectively and 'tansig' transfer function is used for both hidden layer and 'purelin' transfer function is used for output layer that gives the best performance as shown in Fig. 4. The network of fault locator is multi layered feed forward ANN with 9 neurons in the input layer, 24 neuron in first hidden layer, 12 neuron in second hidden layer and 1 neuron in output layer (9-24-12-1) is capable of minimizing the mean square errors (MSE) to a goal of 1* 10^{-07}

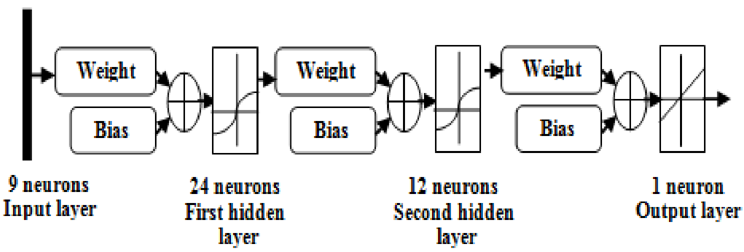

Figure 4: Architecture of ANN Based LLG Fault Locator

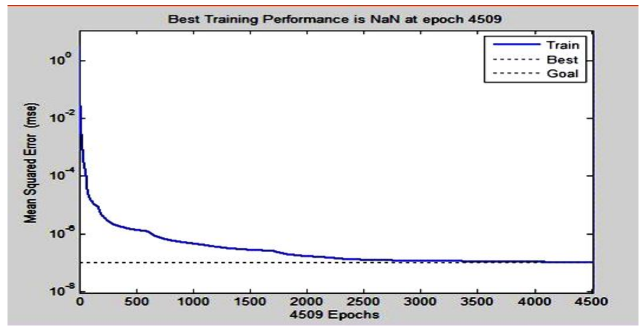

Figure 5: ANN training performance (MSE) for LLG Fault Locator

3) Training for LL Fault: Here two hidden layer of 24 and 12 neuron in first and second hidden layers respectively and 'tansig' transfer function is used for both hidden layer and 'purelin' transfer function is used for output layer that gives the best performance as shown in Fig. 6. The network of fault locator is multi layered feed forward ANN with 9 neurons in the input layer, 24 neuron in first hidden layer, 12 neuron in second hidden layer and 1 neuron in output layer (9-24-12-1) is capable of minimizing the mean square errors (MSE) to a goal of 9.99* 10^{-08} in 2663 epochs as shown in Fig. 7.

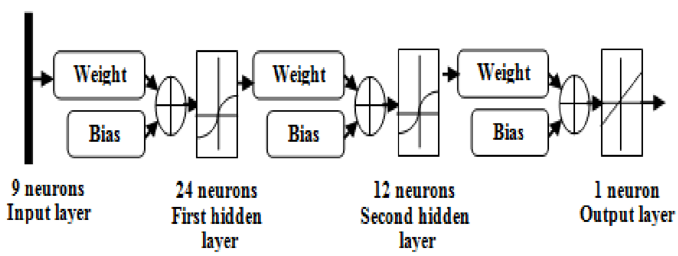

Figure 6: Architecture of ANN Based LL Fault Locator

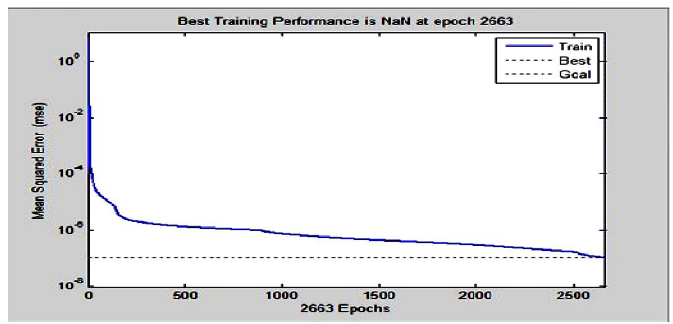

Figure 7: ANN training performance (MSE) for LL Fault Locator

4) *Training for LLL Fault*: Here two hidden layer of 24 and 12 neuron in first and second hidden layers respectively and 'logsig' transfer function is used for both hidden layer and 'purelin' transfer function is used for output layer that gives the best performance as shown in Fig. 8. The network of fault locator is multi layered feed forward ANN with 9 neurons in the input layer, 24 neuron in first hidden layer, 12 neuron in second hidden layer and 1 neuron in output layer (9-24-12-1) is capable of minimizing the mean square errors (MSE) to a goal of 9.92* 10^{-08} in 249 epochs as shown in Fig. 9.

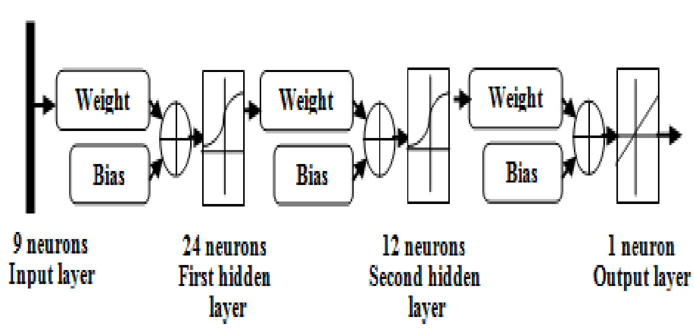

Figure 8: Architecture of ANN Based LLL Fault Locator

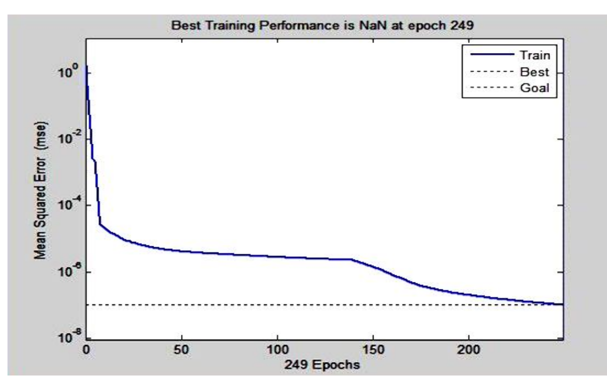

Figure 9: ANN training performance (MSE) for LLL Fault Locator

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ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor:6.887
Volume 5 Issue X, October 2017- Available at www.ijraset.com

IV. TEST RESULTS OF ANN BASED FAULT LOCATOR

After training the networks of all phase to phase and phase to ground faults, we need to test the trained network to check networks are properly trained or not. Test dataset is generated at different fault parameter which is not used during training pattern generation.After training, the ANN based Fault detector and Fault classifier was then extensively tested using independent data sets consisting of fault scenarios which were never used previously in the training process. For different faults cases of the test data set, fault type, fault location, fault resistance and fault inception angle were changed to investigate the effects of these factors on the performance of the proposed protection algorithm. The network was tested and performance was validated by presenting all types of fault cases with varying fault locations (L_f = 0-99KM), fault resistances (R_f = 0-119Ω) and fault inception angles (Φi = 0-360°). At various locations all types of phase faults and ground faults were tested to find out the maximum deviation of the estimated distance L_f measured from the relay location and the actual fault location L_a. The estimated error is expressed as a percentage of total line length as given in equation (4).

$$\%\ \text{Error} = \frac{\text{Actual Location} - \text{Estimated location}}{\text{Total line length}} \times 100 \qquad (4)$$

The test results of ANN based Fault Locator for ground faults and for phase faults are given in Table 3 and 4. It is clear from the table that the estimated location is approximately same as actual fault location. The maximum and minimum percentage errors of the test result for ground faults are 0.963% and 0.0015% respectively. The maximum and minimum percentage errors of the test result for phase faults are 0.21% and 0.01% respectively.

Fault Type	Fault Resistance Rf (ohm)	Fault Inception angle Φi (deg)	Actual Fault Location Lf (in km)	ANN Output (in km)	% Error
A1G	1	0	2	1.9438	0.05
B1G	25	60	15	15.9448	-0.94
C1G	50	150	35	34.9985	0.0015
A2G	75	210	60	60.1230	-0.123
B2G	100	300	75	74.0370	0.963
C2G	119	360	99	99.0468	-0.04
A1B1G	5	0	2	1.3731	0.62
B1C1G	50	150	35	35.007	0.007
A1C1G	60	180	48	48.8888	0.88
A2B2G	75	210	60	59.8464	0.15
A2C2G	100	300	75	74.94	0.05
B2C2G	119	360	99	99.1823	-0.18

Table 3: Test results of ANN based Fault Locator for Ground Faults

Fault Type	Fault Resistance R_f (ohm)	Fault Inception angle Φi (deg)	Actual Fault Location L_f (in km)	ANN Output (in km)	% Error
A1B1	0.01	0	2	1.7834	0.21
A1C1	0.01	45	15	14.8592	0.14
B1C1	0.01	60	30	29.9883	0.01
A2B2	0.01	120	45	45.2005	-0.20
A2C2	0.01	150	50	50.1870	-0.18
B2C2	0.01	210	65	65.0574	-0.05
A1B1C1	0.01	300	80	80.0938	0.09
A2B2C2	0.01	360	99	98.8147	0.18

Table 4: Test results of ANN based Fault Locator for Phase Faults

V. CONCLUSIONS

This paper presents new approaches for the ANN based fault location in double circuit transmission line using only one terminal data, which can be used in the digital protection of the double circuit power transmission system. These approaches are based on fundamental components of three phase voltages and the six phase currents of the two parallel lines which is given as input to the artificial neural network for fault location task. The protection scheme effectively eliminates the effect of varying fault resistance, fault location and fault inception angle. The performance of the proposed scheme has been investigated by a number of offline tests. The complexity of all the ten types of faults in both the circuit of double circuit transmission line, fault locations (0-100%), fault inception angles (0-360°) and fault resistances (0-120Ω) are considered. The proposed protection scheme allows the protection engineers to increase the reach setting i.e. greater portion of line length can be protected as compared to earlier conventional techniques. This ANN based technique does not require communication link to retrieve the remote end data.

VI. ACKNOWLEDGMENT

I would like to sincerely thank Mr. Jitesh Panigrahi, Assistant Professor (Dept. of E.E.) who provided expertise that greatly assisted the research work.

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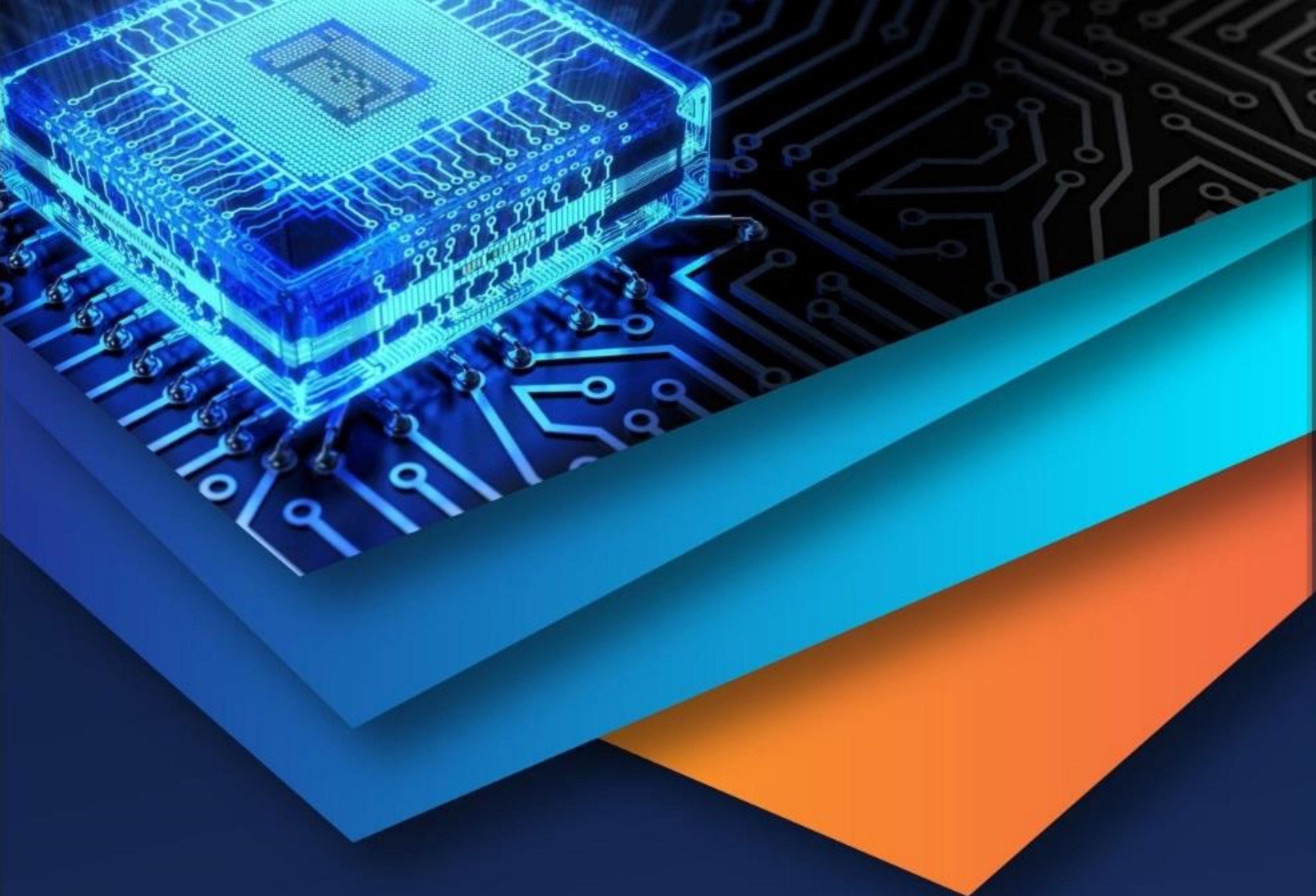

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