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An Accurate Fault Detection and Classification Algorithm for Double Circuit Transmission Lines Using Artificial Neural Network

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Abstract: This paper presents a new and accurate fault detection and classification strategy for double circuit transmission lines based on artificial neural network. The mutual coupling effect in double circuit transmission lines causes problems to the conventional protection relays. The nonlinearity of this effect can be solved by artificial neural networks by identifying different impressions of the fault current signals. The proposed protection method uses only the post fault current signals amplitudes from the sending end of line for the detection and classification of all types of the faults. The proposed protection method is evaluated under several fault conditions such as the fault inception angle, the fault resistance and the fault location. Thus, simulations under MATLAB environment were made on a 220KV double circuit transmission line and the simulation results show that the suggested method is able to detect and classify all possible faults to know phase-ground, phase-phase, phase-phase-ground and three-phase with a high accuracy degree under varying system conditions.
Keywords: Double circuit transmission line, Discrete Fourier transform (DFT), Artificial neural network (ANN), Fault detection (FD), Fault classification (FC), Fault inception angle (FIA).

I. INTRODUCTION

Doubles circuit transmission lines are being most widely because it has enhanced power transmission capability and it increases the reliability of the system. Various types of faults known as phase-ground, phase-phase, phase-phase-ground and three-phase faults occurs in Double circuit Transmission lines. Due to parallel transmission line the numbers of fault cases are twenty and hence a very accurate and fast detection and classification of these faults are necessary under various system fault situations for the service restoration and reliability. In parallel transmission lines, faulty phase(s) of one circuit has an effect on the healthy phase(s) of the parallel circuit due to mutual coupling effect which cause difficulty in the classification of faults using traditional methods.

Many fault detection and classification approaches for double circuit transmission lines were proposed in the literature. Most of these approaches are principally based on the voltage and current signals amplitudes which are measured from the relay location. Presently, in the new protection approaches the artificial intelligence tools like artificial neural networks (ANN), fuzzy logic system (FLS), and adaptative network based fuzzy inference system (ANFIS) are being used, which are promising alternatives compared to the conventional techniques. The authors in paper [1] have proposed a fault classification method only for the LG faults and LLG faults but the suggested technique did not specify the phase affected. The authors in paper [2] have presented an ANN based fault classification method for double end fed parallel transmission lines in which the voltage and current signals available at only the sending end of line was used, but this reported method classifies only line-to-line fault. Other works [3]-[5] were based on application of ANN which proves to be accurate in the detection and the classification of fault types.

An artificial neural network based fault detection and fault classification algorithm has been developed in this presented work. This protection algorithm is an accurate method for fault detection and classification of double circuit transmission lines which uses only amplitude of current signals from sending end side considering the effects of variation in fault resistance, fault location, and fault inception angle. Different offline fault cases have been simulated to investigate its performance in terms of accuracy and robustness.

II. POWER SYSTEM NETWORK SIMULATION

A. The System Studied

The single line diagram of double-circuit transmission line connected to the three phase source at both the ends is shown in Fig. 1. The studied network has been simulated using Simulink and SimPowerSystem toolbox of MATLAB. The parameters of the power system model of Fig. 1 are as follows [2]:

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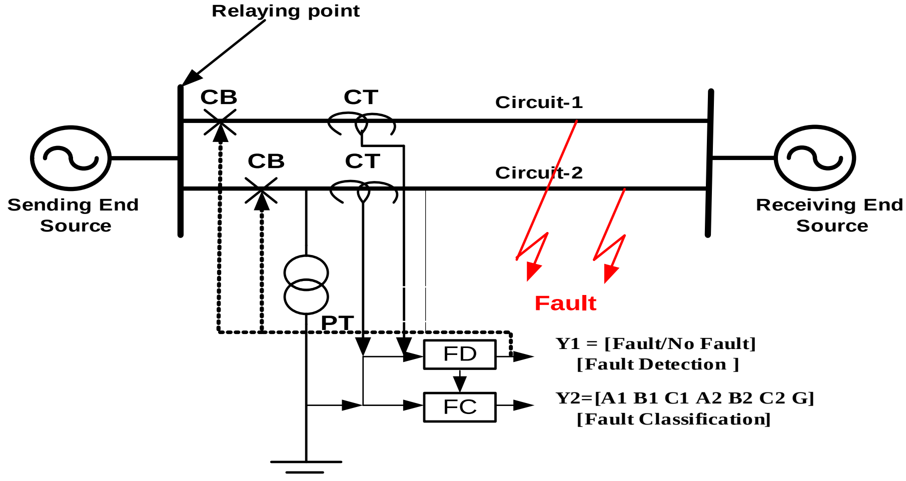

Figure 1: Single line diagram of simulated power system network

Table 1: Parameters of Double Circuit Transmission Line

Components	Parameters		
Three phase source	Voltage (kV)		220
	Frequency(Hz)		50
	Short circuit capacity (GVA)		1.25
	X/R ratio		10
Transmission line	Line length (km)		100
	Line voltage (kV)		220
	Sequence impedance (Ω/km)	Positive	0.0181 + j0.292
		Zero	0.2188 + j1.031
		Zero sequence mutual	0.20052 + j0.6535
	Sequence capacitance (nF/km)	Positive	12.571
		Zero	7.8555
		Zero sequence mutual	-2.0444

B. Typical Primary System Waveforms

The waveforms of three phase current signals under the occurrence of "A_1B_1G" fault which is 10 km away from the sending end bus with fault resistance of $R_f = 1\Omega$ and fault inception angle of $\Phi_i = 0^o$ are shown in Fig. 2 and 3. It is very clear from Fig. 2 that after occurrence of "A_1B_1G" fault there is significant change in magnitude of current signals of A phase and B phase of faulty circuit As expected, there is a change in magnitude of A and B phases of healthy circuit 2 due to the mutual coupling effect between these two circuit as shown in Fig. 3.

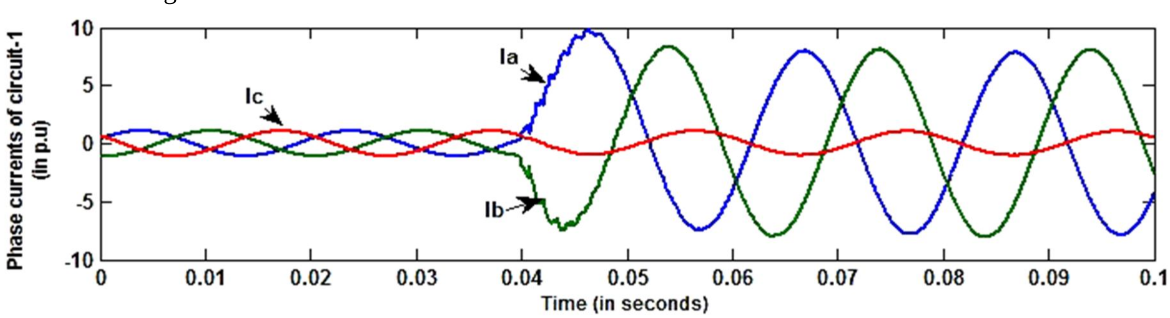

Figure 2: Waveforms of current signals of faulty circuit 1 on A_1B_1G fault at 10 km with $R_f = 1\Omega$ and $\Phi_i = 0^o$

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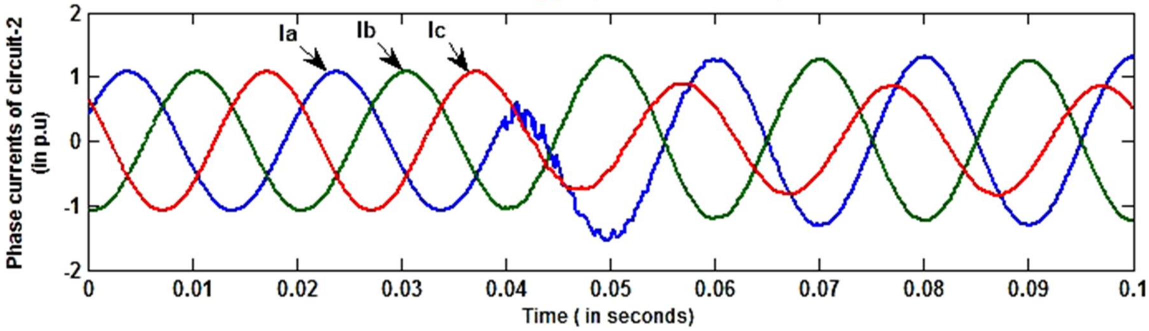

Figure 3: Waveforms of current signals of healthy circuit 2 on A_1B_1G fault at 10 km with $R_f = 1\Omega$ and $\Phi_i = 0^o$

III. ANN STRUCTURES FOR FAULT DETECTOR AND FAULT CLASSIFICATION

A. Inputs and Outputs

To detect the occurrence of fault in the line an ANN based fault detector is designed. The magnitudes of each fundamental current signals recorded at the relay location are evaluated by using discrete Fourier transform and the magnitudes of these current signals are used to calculate the characteristic features which will be the input for ANN. The characteristic features are calculated in terms of Δ1, Δ2, Δ3 for circuit 1 and Δ11, Δ22, Δ33 for circuit 2, which are calculated as described below. First of all, from the post-fault current samples the ratios *r*1, *r*2 and *r*3 for circuit 1 and r11, r22, and r33 for circuit 2 are calculated as follows:

$$r1 = \max\{abs(Ia1)\} / \max\{abs(Ib1)\} \qquad r11 = \max\{abs(Ia2)\} / \max\{abs(Ib2)\}$$
$$r2 = \max\{abs(Ib1)\} / \max\{abs(Ic1)\} \qquad r22 = \max\{abs(Ib2)\} / \max\{abs(Ic2)\}$$
$$r3 = \max\{abs(Ic1)\} / \max\{abs(Ia1)\} \qquad r33 = \max\{abs(Ic2)\} / \max\{abs(Ia2)$$

where Ia1, Ib1, Ic1 are the post-fault samples of the three phase currents of circuit 1 and Ia2, Ib2, Ic2 are the post-fault samples of the three phase currents of circuit 2.Next, the normalized values of *r*1, *r*2, *r*3, *r*11, *r*22 and *r*33 are found out as follows:

$$r1n = r1 / \max(r1, r2, r3) \qquad r11n = r11 / \max(r11, r22, r33)$$
$$r2n = r2 / \max(r1, r2, r3) \qquad r22n = r22 / \max(r11, r22, r33)$$
$$r3n = r3 / \max(r1, r2, r3) \qquad r33n = r33 / \max(r11, r22, r33)$$

Finally, the differences of these normalized values are found out as follows.

$$\Delta1 = r1n - r2n \qquad \Delta2 = r2n - r3n \qquad \Delta3 = r3n - r1n$$
$$\Delta11 = r11n - r22n \qquad \Delta22 = r22n - r33n \qquad \Delta33 = r33n - r11n$$

These six features Δ1, Δ2, Δ3, Δ11, Δ22, Δ33 are used as the input information to train the proposed neural network. The fault detector function is to detect whether fault is present in the line or not, hence neural network for fault detector gives only one output either '0' or '1' where '0' represents no fault case and '1' represents fault case. Hence the input vector for neural network of fault detector is given by $X_{F\text{-}det}$ and the output of neural network of proposed fault detector is given by $Y_{F\text{-}det}$.

$$X_{F\text{-}det} = [\Delta_1, \Delta_2, \Delta_3, \Delta_{11}, \Delta_{22}, \Delta_{33}] \qquad Y_{F\text{-}det} = [\text{Fault/No fault}]$$

similarly, the fault classifier function is to identify the faulty phase(s), hence seven outputs (six for different phases of parallel circuits and one for detection of presence of ground) are taken as neural network outputs for fault classifier. Hence the ANN input vector $X_{F\text{-}class}$ and ANN output vector $Y_{F\text{-}class}$ for the fault classification are given as:

$$X_{F\text{-}class} = [\Delta_1, \Delta_2, \Delta_3, \Delta_{11}, \Delta_{22}, \Delta_{33}] \qquad Y_{F\text{-}class} = [A_1, B_1, C_1, A_2, B_2, C_2, G]$$

B. Design process

The number of inputs and outputs in the ANN of fault detector and classifier was decided then the number of layers and the number of neurons in each layer was to be considered. After analyzing different neural networks with combinations of activation functions, it was decided to use a four layers neural network with 6 neurons in the input layer, 12 neurons in the first hidden layer and 8 neurons in the second hidden layer and 1 neuron in the output layer (6-12-8-1) for fault detection as shown in Fig. 4. After analyzing different transfer functions 'logsig' transfer function was used for both hidden layer and for output layer 'purelin' transfer function was used in neural network of fault detection task.

However for fault classification, four layers network with 6 neurons in the input layer, 24 neurons in the first hidden layer, 20 neurons in the second hidden layer and 7 neurons in the output layer (6-24-20-7) was found to be suitable as shown in Fig.

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5.'Logsig' transfer function was used for both hidden layers and for output layer 'purelin' transfer function was used in neural network of fault classifcation task.

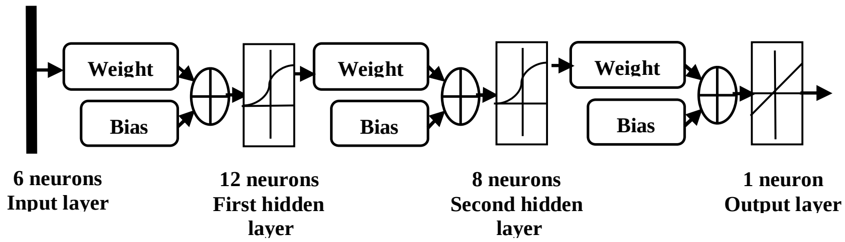

Figure 4: Architecture of ANN Based Fault Detector

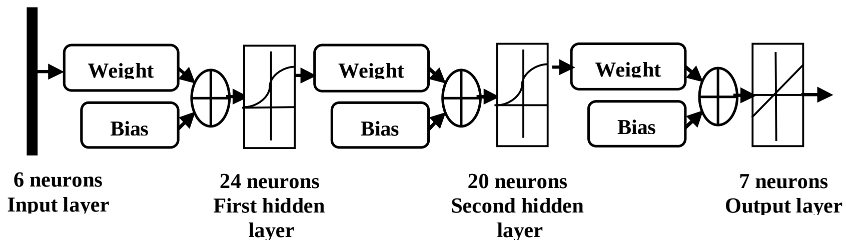

Figure 5: Architecture of ANN Based Fault Classification

C. Training process

The Training data set is necessary for appropriate training of ANN hence the training data set for fault detection and classification task were generated for all possible faults types such as phase-ground, phase-phase, phase-phase-ground and three-phase under varying system conditions that is at different fault locations, fault inception angles and fault resistance. The types of fault, fault locations, fault resistances and fault inception angle used for preparing training data set are shown in table 2.

Table 2: Training Data Pattern Generation

Parameters	Set Value
Type of Faults	A_1-G, B_1-G, C_1-G, A_1-B_1-G, B_1-C_1-G, C_1-A_1-G, A_1-B_1, B_1-C_1, C_1-A_1, A_1-B_1-C_1, A_2-G, B_2-G, C_2-G, A_2-B_2-G, B_2-C_2-G, C_2-A_2-G, A_2-B_2, B_2-C_2, C_2-A_2, A_2-B_2-C_2
Fault Location	1,3,7,10,15,25,40,55,70,85,99
Fault Resistance	1,50,100,150 Ω (for ground fault) & 0 Ω (for phase fault)
Fault Inception Angle	0^o & 90^o

Hence the total numbers of fault cases simulated for phase(s) to ground fault are 12 x 11 x 4 x 2= 1056 and the total numbers of fault cases simulated for phase(s) to phase fault are 8 x 11 x 1 x 2= 176. Therefore the total number of training patterns generated for fault detection task is 1232(fault cases) + 1(no fault case) = 1233 and 1232 for fault classification task. Levenberg– Marquardt (LM) training algorithm was used for training of neural networks of both fault detector and fault classifier. This learning method converges very quickly and hence the mean squared error (mse) decreases to 4.36e-09 in 31 epochs for fault detector as shown in figure 6 and for fault classifier the mse decreases to 9.34e-05 in 168 epochs as shown in figure 7.

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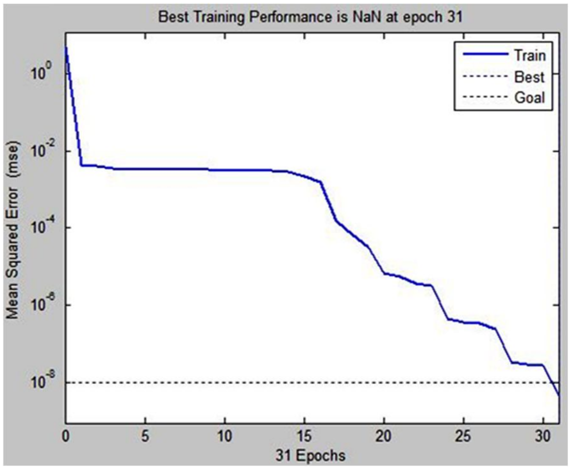

Figure 6: MSE performance for fault detector

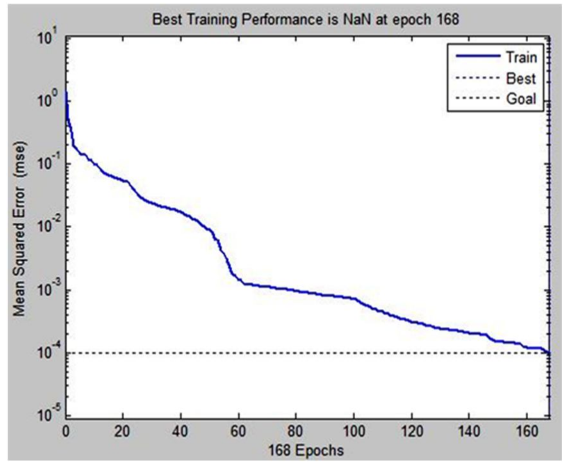

Figure 7: MSE performance for fault classifier

IV. RESULTS OF ANN BASED FAULT DETECTOR AND FAULT CLASSIFIER

After finishing the training process, the accuracy of the trained neural network was extensively tested using independent test data sets which consisting of different fault scenarios that had not been used previously in training process. Test data sets were generated for different fault types by varying fault resistance R_f, fault inception angles Φi and fault location L_f for investigating the effect these parameters on the performance of the proposed protection technique. The neural network was extensively tested and validated by providing different fault scenarios by varying fault resistance R_f (0-145 Ω), fault locations L_f (0-99 km) and fault inception angles Φi (0-360°).

Table 3: ANN based Fault Detector & Classifier test results

Fault Type	Fault resistance R_f (ohm)	Fault inception angle Φi (deg)	Fault Location L_f (in km)	ANN Output						
				A1	B1	C1	A2	B2	C2	G
A1G	2	0	2	0.99	0	0	0	0	0	0.99
C1G	60	30	15	0	0	1	0	0	0	0.99
A2G	95	60	30	0	0	0	0.99	0	0	1
B2G	145	90	45	0	0	0	0	1	0	0.99
A1C1G	60	180	80	1	0	1	0	0	0	1
B2C2G	95	270	90	0	0	0	0	1	1	0.99
A2C2G	145	360	99	0	0	0	1	0	1	1
A1C1	0.01	0	2	1	0	1	0	0	0	0
A1B1	0.01	90	15	0.99	0.99	0	0	0	0	0
A2B2	0.01	150	30	0	0	0	0.98	1	0	0
A1B1C1	0.01	300	60	0	0	0	1	1	0	0

From the test results given in Table 3, it is clear that the developed ANN based Fault Detector and Classifier is able to detect and classify the fault rapidly and accurately. Thus, even the extreme fault cases of high fault resistance near the far end of the line was detected and classified rapidly by the developed ANN based Fault Detector and Classifier.

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V. CONCLUSIONS

An accurate fault detection and classification technique using ANN has been proposed, which can be implemented for the digital protection of the double circuit power transmission line. The protection algorithm employs the three phase current signals of both the circuit-1 and circuit-2 as input for the corresponding neural network for fault detector and fault classifier. The proposed protection algorithm effectively eliminated variations in fault resistance, fault location and fault inception angle. The performance of the proposed scheme was tested for large numbers of offline test cases in which all possible types of faults with variations in fault resistance R_f (0-145 Ω), fault location L_f (0-99 km) and fault inception angle Φi (0-360°) were considered . The simulation test results concludes that the proposed ANN based Fault Detector and Fault Classifier can be implemented to support a new generation of protective relay systems at faster speed with high accuracy.

VI. ACKNOWLEDGMENT

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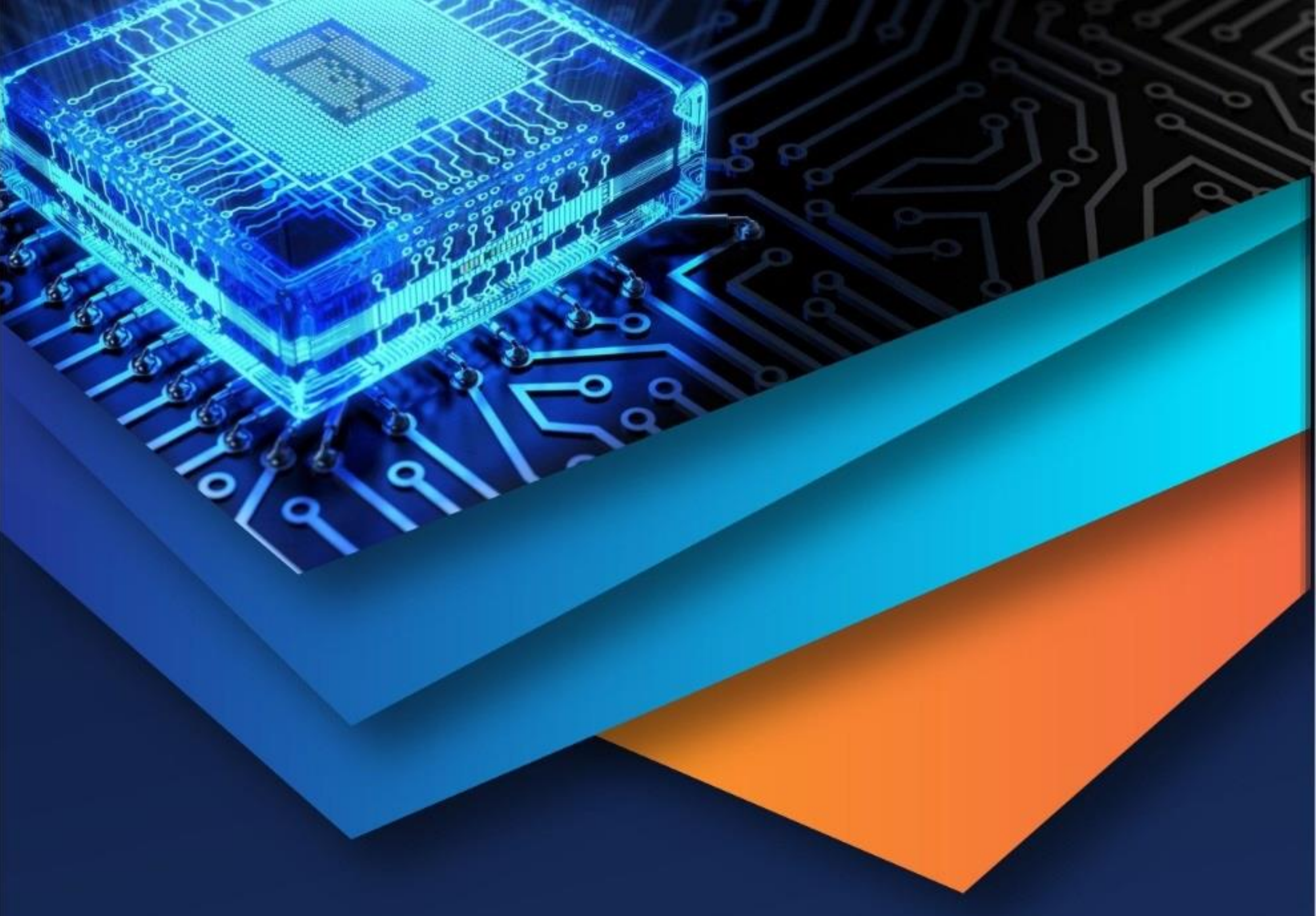

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