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Prediction of Corrosion Rates in Structural Steel Using Artificial Neural Networks

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Abstract: A phenomenal outcome for the prediction of corrosion in steel was proposed with the learning ability of artificial neural network using MATLAB software. The prediction of corrosion rate has become an important challenge for the Indian steel industry as well as for the engineering community. This paper presents the studies carried out towards the prediction of corrosion rates by using artificial neural networks (ANN), in which training of 406 sets of data using Levenberg-Marquardt algorithm obtained from experimental data. The training sets have been developed for three levels of corrosion such as mild, moderate and severe through ANN and resulted in a trend of an incremental parabolic curve. The input parameters considered were equivalent to simulate corrosion of structural steel exposed to atmospheric, marine or chemical environment. The correlation statistics (R) in ANN has proved to be 90%. The test results have been validated to confirm the efficacy of developed ANN model for prediction of corrosion rate.
Key words: Corrosion, Artificial neural networks (ANN), Levenberg-Marquardt algorithm

I. INTRODUCTION

A major cause of deterioration of steel structures exists as part of our everyday life. Corrosion damage can also results in life threatening situations, hence it has to be addressed for safety, environment and economic reasons. Corrosion of steel is an electrochemical process which causes the degradation of material. Steel structures exposed to the extreme atmosphere, especially marine and highly polluted industrial environment are subjected to corrosion. It is more important for the Engineering community to understand about the durability of protective coating and the consequences of loosing this protective coating leads to increase in its corrosion depth. There are different forms of corrosion as shown in Fig.1. And one of them which commonly occur is uniform corrosion which results in reduction in the weight and thickness. Other forms of corrosion are Crevice corrosion which forms under the limited atmospheric fluid, bacterial corrosion, galvanic corrosion etc.

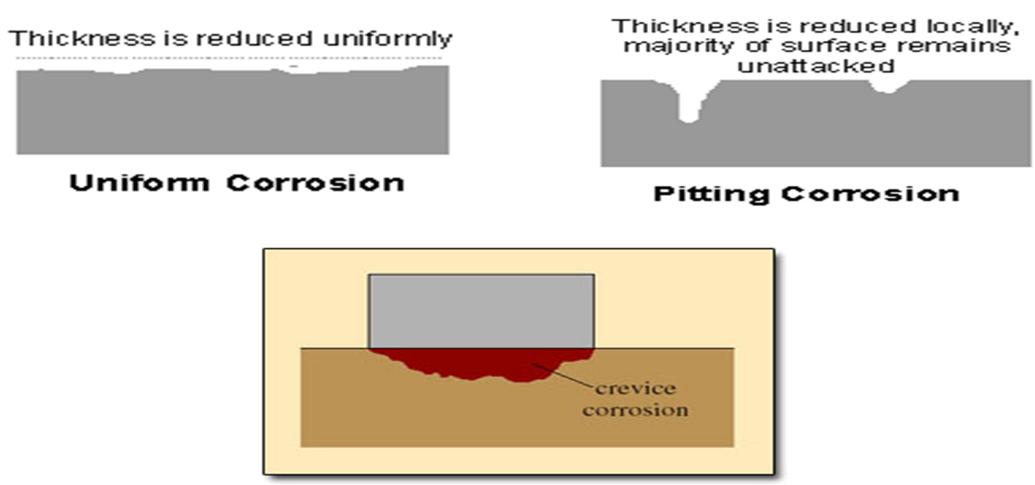

Fig.1.Different forms of corrosions

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It is well documented that atmospheric corrosion rates are affected by environmental conditions, yet the majority of corrosion models predict corrosion loss as a function of time only. Previous studies have expressed corrosion loss as a power model.

$$C=At^n \qquad \text{----------- (1)}$$

Where C=mass loss caused by corrosion per unit of the exposed area; *t* exposure time; *A* proportionality constant; and *n* mass loss exponent (Robert., 2006). The five environmental factors of interest are the time of wetness TOW, sulphur dioxide, chloride, exposure time and the air temperature. To accomplish the goal of this research project, three research objectives were defined: 1) formulation of model components, 2) calibration of the environmental factor coefficients; and 3) validation of the effects of the environment on atmospheric corrosion using independent data.During the last decades the researchers have proposed the prediction of corrosion through various experiments which results that corrosion in steel causes the loss of thickness and weight loss(Cinitha et al., 2014) summarized forms of corrosion with its model and described the depth of corrosion. The estimation of corrosion rate for long term are always based on time and areas (Dawn et al., 2007) results the calibration and validation of models with respect to time dependent models (Kexi et al., 2012) showed that the Genetic algorithm and Back propagation ANN yields the smallest number of absolute errors and should be selected as the preferred model for predicting the corrosion rates. (Hernandez et al.,2005) agreed both wetability and changes in brine chemistry to be the major ways because of which crude oil affects the corrosion of carbon steels. Results showed (Aprael., 2008) that neural networks are a powerful tool and its validity of the results was closely linked to the amount of data available with the experience and the knowledge that accompany the analysis. Long term corrosion is severe in the industrial and marine atmospheres as compared to rural and urban atmospheres (Fuente et al., 2008).

II. ARTIFICIAL NEURAL NETWORKS

The objective chosen here for the study is to predict the corrosion rates through ANN modeling.ANN has to be feed with input data's and number of hidden layer varies depending upon the trails for obtaining the fitted output. The data has to be collected and trained in the toolbox until fitted data's are obtained (Cai et al.,1999). A key advantage of the ANN is its ability to learn, recognize, generalize, classify and interpret incomplete and noisy inputs (data). The ANN can acquire information about a given process through data in the training phase. This information is then stored in numerical form within the weights. One distinguishing characteristic of an ANN is their adaptability, which requires a unique information flow design as shown in Fig.2.

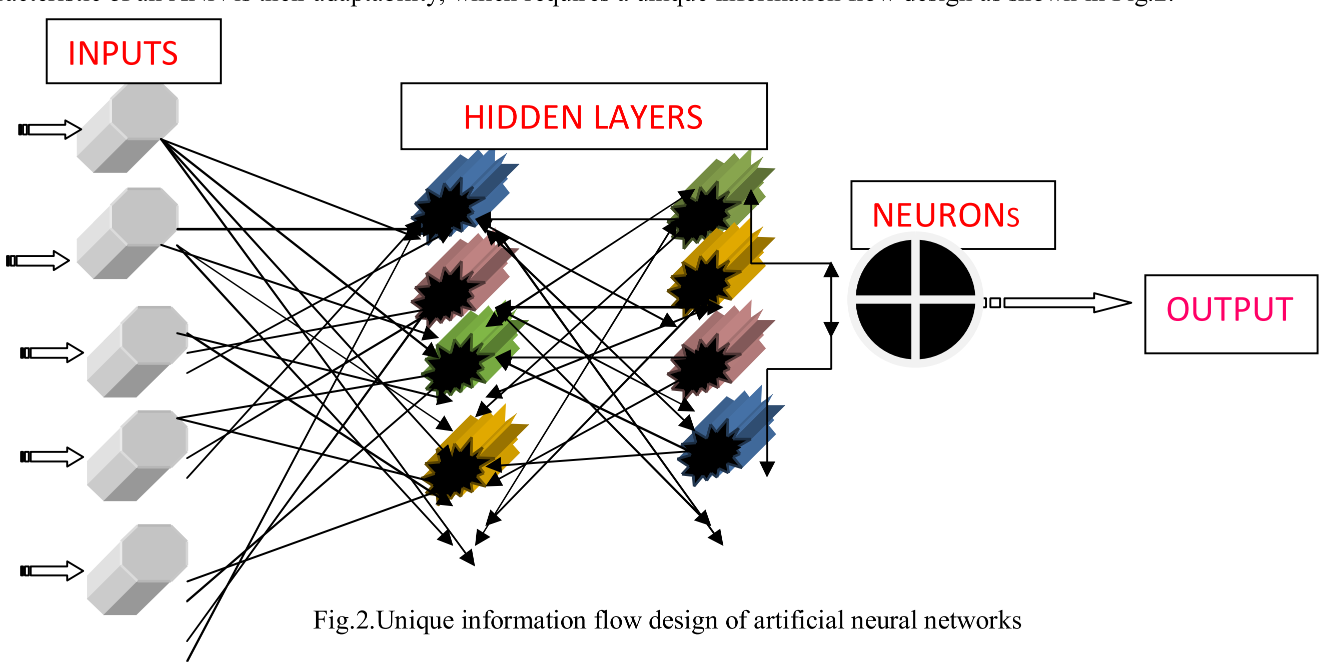

Fig.2.Unique information flow design of artificial neural networks

A. Properties of Artificial Neural Nets (ANNs)

Highly parallel, distributed processing, Learning by tuning the connection weights are some of the basic properties of ANN. Basic

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flow in Fig.3 for designing artificial neural network model is shown. The Neural Network Toolbox is one of the commonly used, powerful, commercially available software tools for the development and design of neural networks. The software is user-friendly, permits flexibility and convenience in interfacing with other toolboxes in the same environment to develop a full application.

A hidden layer neuron adds up the weighted input received from each input neuron ($x_j w_j$) and associates it with bias (b) i.e.,

$$U = \sum_{j=0}^{m} x_j w_j \text{ - b and } V=f(U). \quad \text{------------- (2)}$$

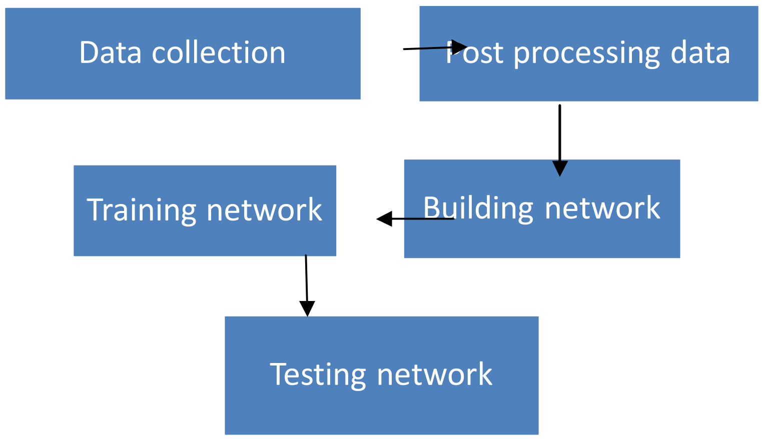

Fig.3.Basic flow for designing artificial neural network model

whereX = (x_1, x_2. . .xn) represent the n input applied to the neuron.
w_j= the weight for input $x_j$and b is a bias& V= output vector

The linear sum (U) is then transformed using a non-linear transfer function (activation function-logistic sigmoid function to produce an output. The output neurons, using linear or nonlinear transfer function do the same as in hidden neurons. This process is a feed-forward propagation of signals through their network. The back propagation algorithm finds the optimal weights by minimizing sum of squares error which has the following form.

$$\text{ERROR} = \sum p \sum_{\rho} (y - t)^2 \quad \text{------------ (3)}$$

Where y = component of network output vector V
t = component of target output vector t
p = number of output neurons
ρ= number of training patterns

III. CORROSION PREDICTION MODEL

The prediction of corrosion rates in structural steel, towers or any industrial buildings, have to be determined based primarily on its parameters which are the root cause for the corrosion rates. The data used for model development in the training and testing stages have been collected from literature (Cai et al., 1999). The data base consists of 407sets of data which have been classified (Cinitha et al., 2014) under mild, moderate and severe conditions.

IV. DATA DISTRIBUTION

ANN provides with intelligent results on training data but requires that the trained network should be tested with independent data sets which have not been used for training (Peterzhang,2007). The available data are divided into three sets: training set, validation set and testing set. From the corrosion map obtained conditions for mild (<20µm), moderate (20-100 µm) and severe (100-200 µm) have been classified with the experimental data sets. In the present paper the training, validation and testing set have been divided with 75%, 15%,and 10% depending upon its trails.

V. SELECTION OF INPUT PARAMETERS

An important step in model development was in determination of variables that affects the corrosion in steel. The variables which affects are the time of wetness, sulphur content, chloride content, air temperature and exposure time. Corrosion prediction has following range of variable and these are used in study in Table.1. (Cai et al.,1999).

Table.1.Variables Used

S.NO	INPUT VARIABLES	SMALLEST VALUE	MAXIMUN VALUE
1.	Corrosion depth(µm)	5	1804.4
2.	Temperature(ºC)	-3.03	27.9
3.	TOW(annual fraction)	0.01	0.95
4.	SO_2 (µg SO_2 m $^{-3}$)	0	171
5.	Chloride (mg CL^- m^{-2} d^{-1})	0	641
6.	Exposure time (years)	0.5	62

VI. RESULTS AND DISCUSSIONS

The results obtained from vigorous training in ANN have been summarized in Table.2 which discusses the correlation values. The three conditions based on mild, moderate and severe has been plotted in Fig.4.The correlation statistic (R) which has evaluated the linear correlation obtained a good result in training, validation and testing. This proves that ANN being an intelligent tool have trained and obtained an output result for given input parameters. And thus this paper has stimulated with the information that ANN excels in predicting the corrosion rates for any number of years.Fig.5.shows the correlation (R) values on bases of its training, validation and testing period.

Table.2.Correlation Statistics (R) values

PERFORMANCE OF correlation statistics(R)	**TRAINING**	**VALIDATION**	**TEST**	**AVERAGE**
MILD	O.90422	0.95345	0.94210	0.91731
MODERATE	0.95739	0.92386	0.81058	0.94074
SEVERE	0.80976	0.89569	0.93956	0.82672

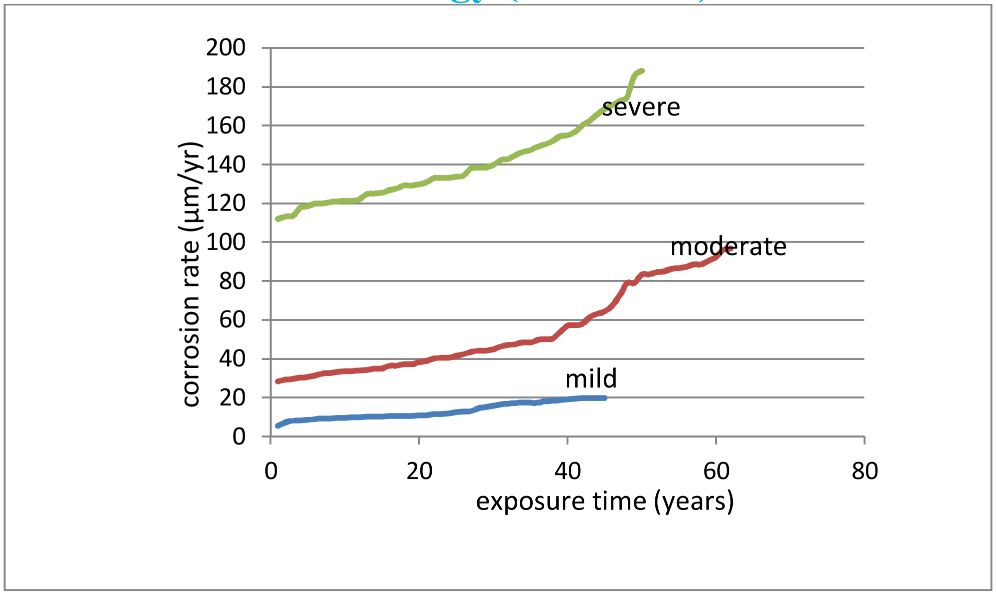

Fig.4.Graph of different conditions

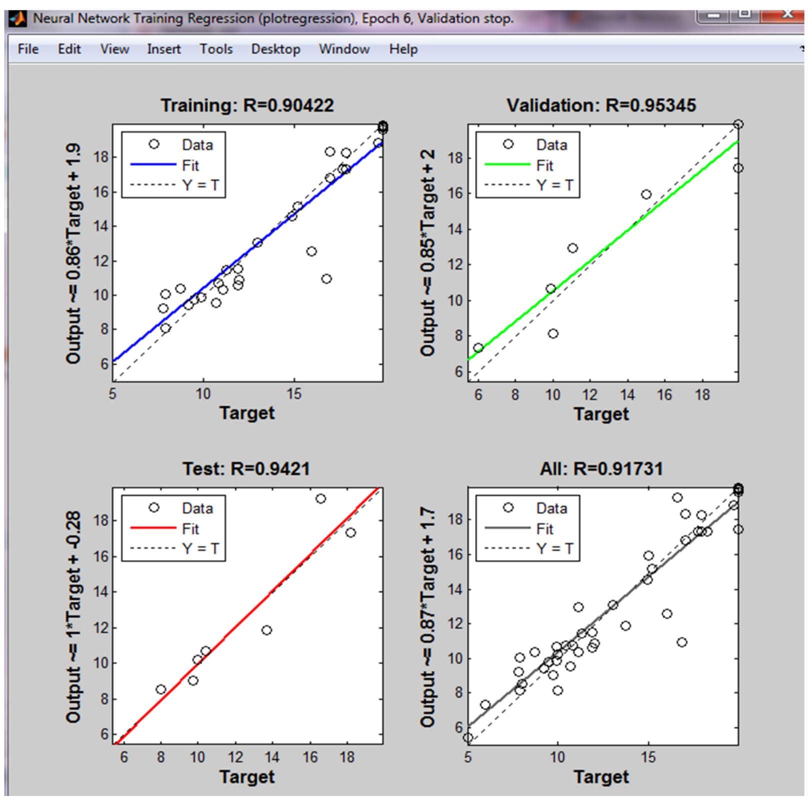

Fig.5a).Predicted correlation statistic for mild condition

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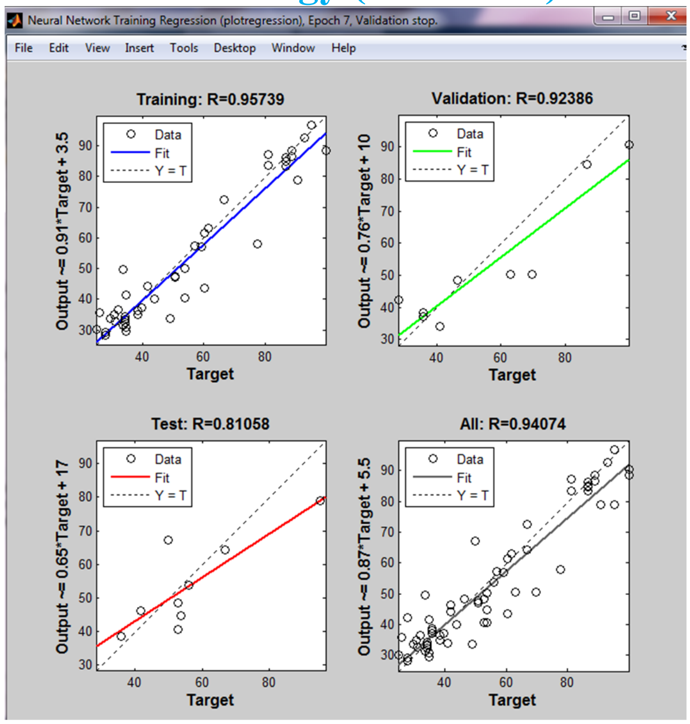

Fig.5b).Predicted correlation statistic for moderate condition

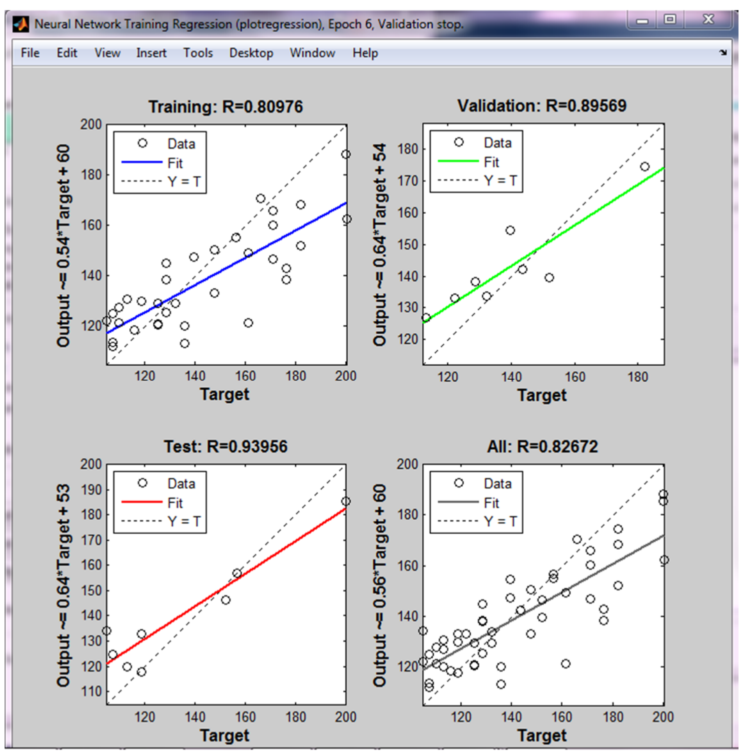

Fig.5c).Predicted correlation statistic for severe condition

VII. CONCLUSIONS

This paper discusses the prediction of corrosion in structural steel using Artificial Neural Network (ANN) trained with Levenberg-

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Marquardt algorithm. From the graph it is observed that with the exposure time(yrs), the consistency was maintained for two to three years and then later an increase in its depth of corrosion (µm/yr). The correlation statistics (R) in ANN have proved to be more than 90% as its test result and that corrosion prediction using ANN stimulated a good accuracy. With the changes in mild, moderate and severe conditions, an incremental parabolic trend is predicted. These three conditions have been put together in graph to check for the change in the environment causing changes in its corrosion rates. Further ANN has satisfied its efficacy and benefits in all aspects regarding data updating or equation changes.

VIII. ACKNOWLEDGEMENT

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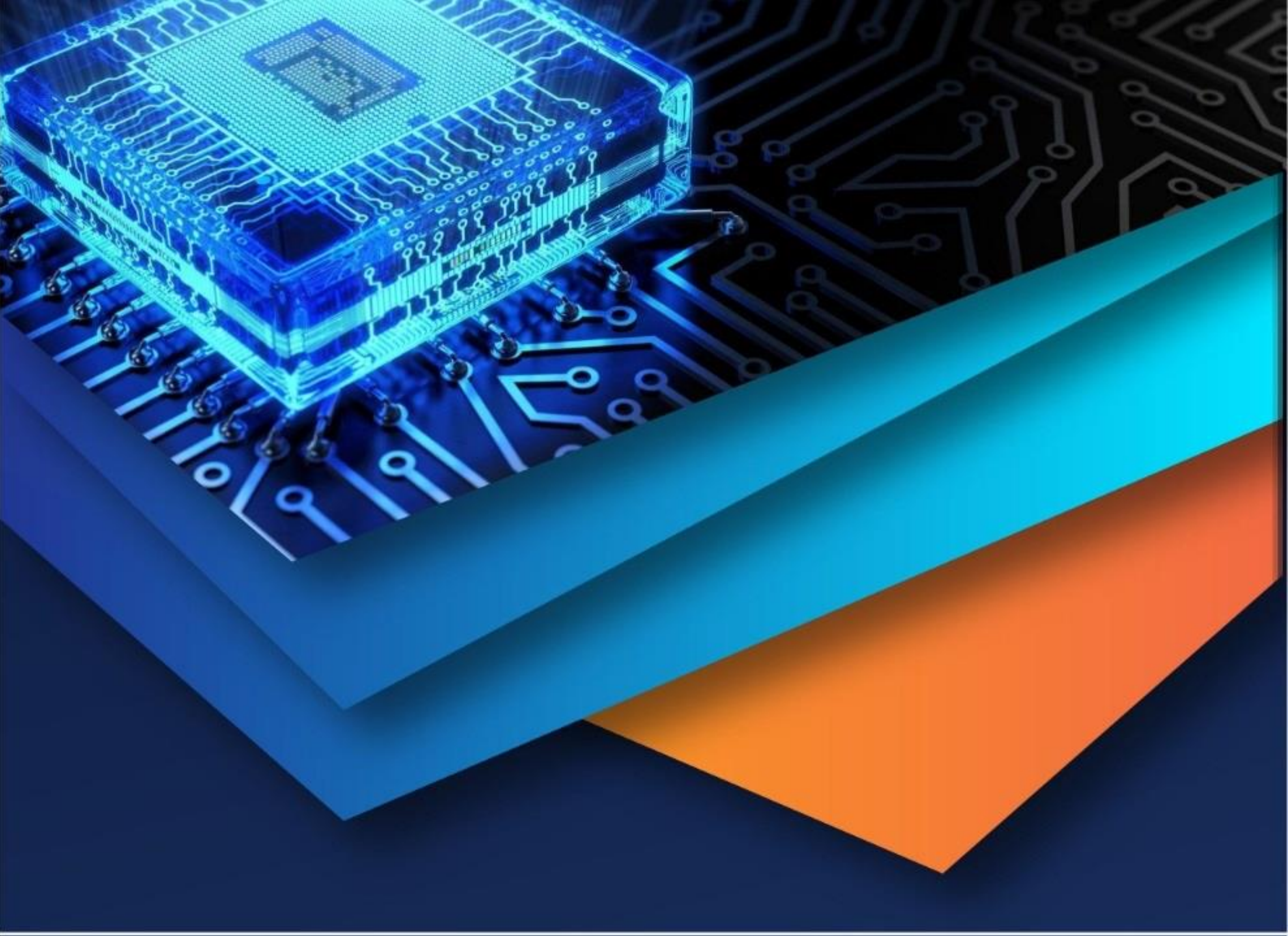

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