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Solar Energy Prediction using Brackpropagation Algorithm in Neural Networks

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Abstract: ***With the rapid depletion of fossil fuels, focus has shifted on renewable sources of energy. Solar energy is has the largest share among all renewable energy sources. However, large scale industries have not embraced solar power due to its fluctuating nature and limited magnitude. Hence large solar power plants are needed to completely replace non-renewable sources.***

This involves large costs and creates dependencies among the customers. Hence, solar energy forecasting becomes mandatory for the establishment, maintenance and planning of large scale solar plants. While conventional statistical techniques have been used thus far for solar irradiation forecasting, yet such techniques suffer from low accuracy. With the advent of artificial intelligence, it is possible to forecast large, non-linear an complex data with high accuracy. This paper presents an artificial neural network based approach for solar irradiation forecasting using the Levenberg-Marquardt back propagation algorithm. It has been shown that the proposed approach attains a mean absolute percentage error of just 2.8%. The low error and high accuracy can be attributed to the efficacy of back propagation in Artificial Neural Networks.

Keywords: Solar Irradiation Forecasting, Artificial Neural Network (ANN), Back Propagation, Levenberg-Marquardt (LM) Algorithm, Mean Absolute Percentage Error (MAPE).

I. INTRODUCTION

Fossil fuels have to major disadvantage presently:

A. They are depleting very fast and hence are not sustainable.
B. They are addition to the already polluted scenario.

Due to growth in population of humans and other evolving technology paradigms, energy consumption has shot off presently. Non renewable sources have been extensively used over the past decades that they need to conserved now and also use of fossil fuels have turned out to be major causes of green house gas emissions and an trigger global warming. Hence we are left with renewable sources of energy as the most viable and beneficial option for meeting the energy demands. Solar Energy is one of such clean sources of renewable energy that can ensure securing and fulfilling the future abundant energy needs. Still large scale industries which consume the maximum amount of power have not migrated to renewable resources of energy due to the following reasons:

1) Fluctuating nature of energy
2) Limited magnitude of energy

Hence it becomes mandatory to establish power plants on a large scale so as to completely migrate from non-renewable to renewable sources. This incurs large costs and hence forecasting of solar irradiation becomes mandatory to such establishments. Artificial Intelligence based systems have the capability of find out patterns in highly non-linear and complex data. Hence it is being used presently for forecasting problems. This paper presents a back propagation based architecture in Artificial Neural Networks for solar irradiation forecasting.

II. INTRODUCTION TO ARTIFICIAL NEURAL NETWORKS (ANN)

A. Basic Properties of ANN

The fundamental properties of the human brain that an artificial neural network tries to copy are:[15]

1) Non-Linear Structure
2) Parallel Architecture
3) Learning and adapting capability.

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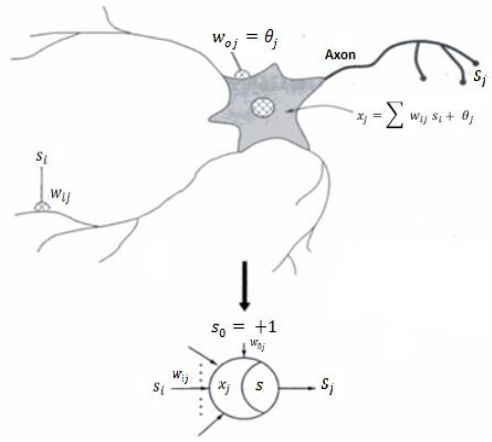

Fig.1 Biological Model of ANN

The ANN learns synonymous with the human brain and is not limited by the human brain's limitations of memory and processing power. This is depicted by the biological model of the ANN in figure 1.

B. Matheatical Model of ANN

The mathematical model of the ANN is derived from its properties of parallel data processing and update of weights or experiences as data is fed to the ANN [19], [11]. Figure 2 depicts the mathematical model of the ANN.

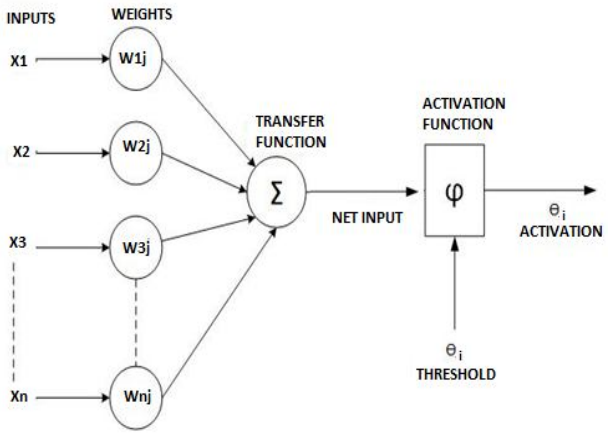

Fig.2 Mathematical Modeling of ANN

The figure above depicts the mathematical model of the ANN.

The fact that the neural network can accept and process data in parallel ensures high speed of operation of the neural network. The learning and adapting capability of the neural network ensures the fact that data can be processed at a high speed. **[2]**These three attributes make the artificial neural network perform tasks generally needing human intervention. The output of and ANN can be given by:

$$Y = \sum_{i=1}^{n} X_i \,.W_i \; + \; \theta_i$$

Here,

y denotes output of the ANN

x denotes the inputs to the ANN

w denotes the weights of the ANN

ϕ denotes the bias.

The neural network needs to be trained before it can be used to predict data and be tested for accuracy. There are several mechanisms to train an ANN but the one that is the most effective in reducing the errors quickly is the mechanism of back propagation.

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III. BACK PROPAGATION IN ANN

A. Back propagation relies on the feedback of errors of the network to the system again. This results in the following attributes of the network

1) Lesser subsequent errors
2) Faster error reduction

Thus back propagation results in lesser errors as well as faster error reduction. The following figure depicts the concept of back propagation.[7]

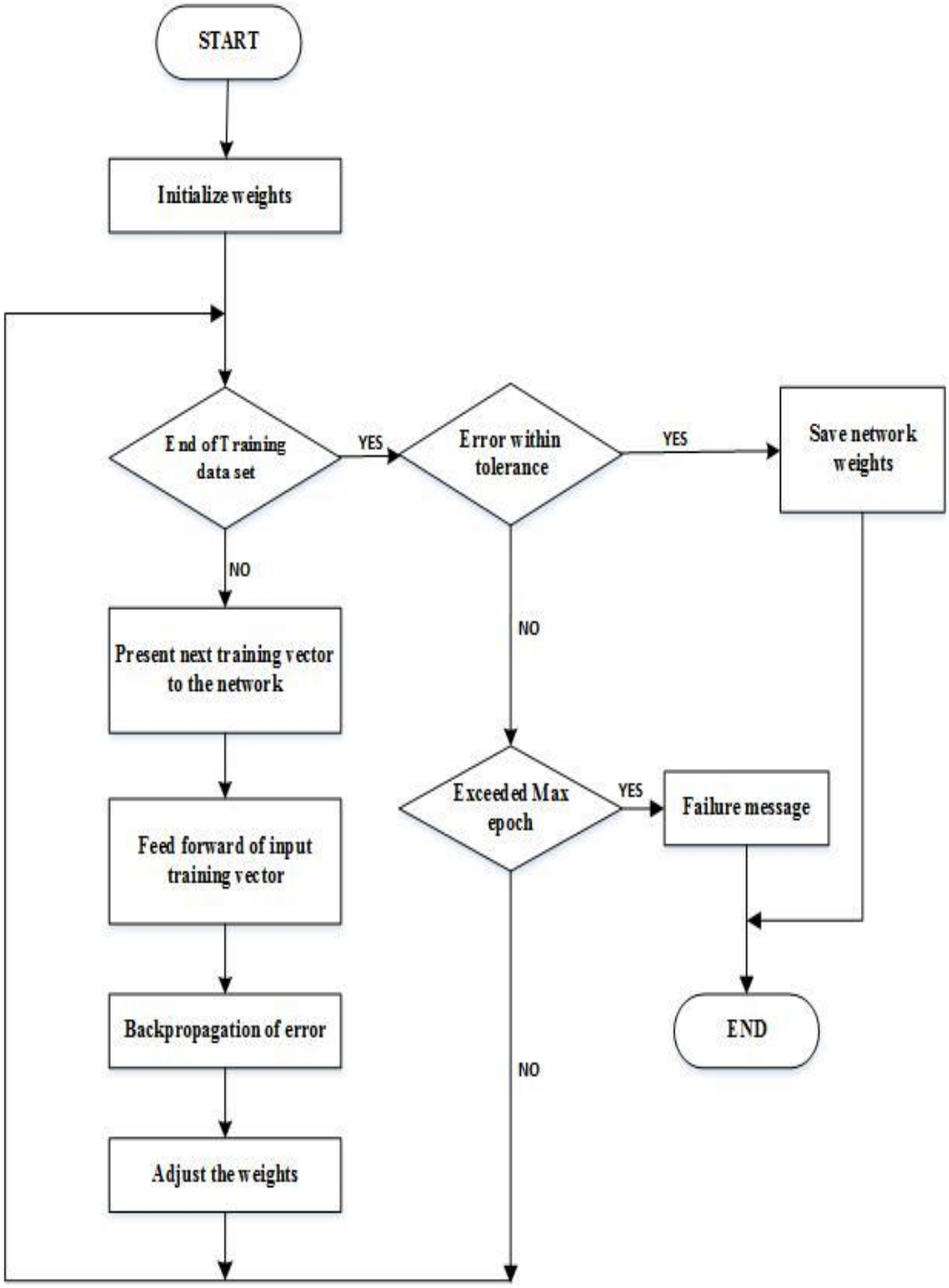

Fig.3 Flowchart of Back Propagation

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B. Back propagation feeds back the errors to the network till the errors do not reduce below a particular limit. This is called the maximum tolerable error. If the system is designed such that the system prediction error does not reduce below the particular tolerable error even after several iterations of training for the pre-defined epochs, failure message is displayed. The three most popular techniques used in back propagation are

1) Levenberg-Marquardt (LM) algorithm.
2) Bayesian Regularization (BR) algorithm.
3) Scaled Conjugate Gradient (SCG) algorithm.

Out of the above, the LM algorithm is the one which shows minimum errors with low execution time i.e. it needs lesser iterations to train. The flowchart of the LM algorithm is shown below:[13]

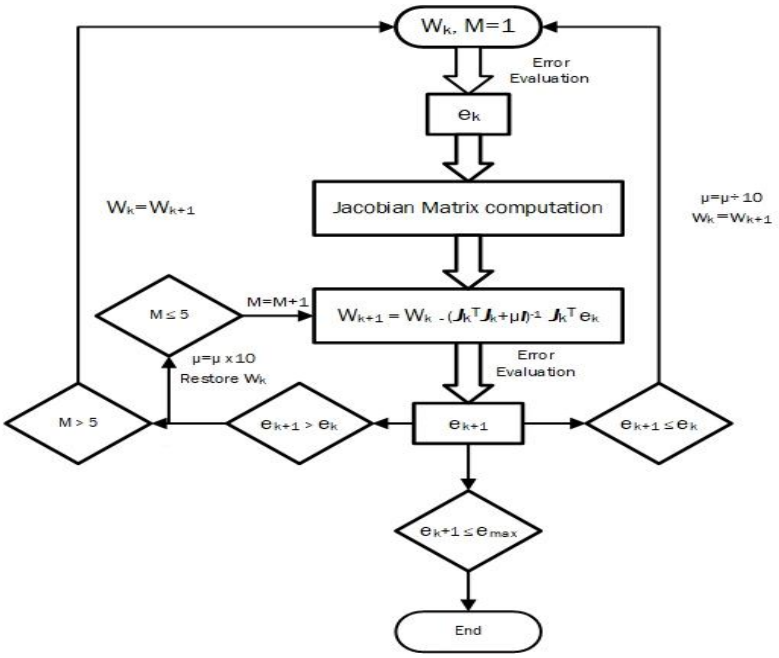

Fig.4 Flow diagram of LM Algorithm

C. The Major Advantage Of The LM Algorithm Is The Fact That It Is Is A Mixture Of The
1) Steepest descent technique and
2) The Gauss-Newton Technique

Algorithm	Rules	Convergence
Gradient Newton algorithm	$W_{k+1} = W_k - \alpha g_x,\ \alpha = \frac{1}{\mu}$	Stable, slow
Gauss – Newton algorithm	$W_{k+1} = W_k - [J_K{}^T J_k]^{-1} J_K{}^T e_k$	Unstable, fast
Levenberg – Marquardt (LM) algorithms	$W_{k+1} = W_k - [J^T{}_k J_k + \mu I]^{-1} J_k e_k$	Stable, fast

Table.1 Comparative Analysis of LM algorithm

The LM algorithm yields both speed and stability of error prediction i.e.

a) It takes lesser time to train an ANN using the LM algorithm

b) The errors keep decreasing with subsequent iterations there by depicting a monotonic decay in errors. The backbone of the algorithm is the computation of the Hessian Matrix using the Jacobian matrix which is the second order rate of change of errors with respect to weights.

The Levenberg –Marquardt algorithm is actually a blend of the steepest descent method and the Gauss–Newton algorithm. The following is the relation for LM algorithm computation,

$$W_{k+1} = W_k - [J_K{}^T J_k + \mu I]^{-1} J_K{}^T e_k$$

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Where,
I indicate the identity matrix,
W_k is the current weight,
W_{k+1} is the next weight of the next iteration
e_k is the last error,
μ is step size deciding number of concurrent inputs to the ANN architecture

IV. SYSTEM DESIGN

The current system uses previous data from Texas Climate Division: (http://mrcc.isws.illinois.edu/CLIMATE/Hourly/StnHourBTD2.jsp) for a period of 26 months (hourly)

A. The Data Is Pre-Processed To Remove
1) Missing values
2) Infeasible values

B. Moreover the Data is Structured to be fed to the ANN in and As
1) Last one hour data
2) Last two hours data
3) Last 24 hours' data
Subsequently, the data is classified into training and testing samples. 70% of the data has been used for training and 30% of the data has been used for testing. The LM algorithm is used for training and simulating the ANN architecture.

C. The Performance Of The Designed Approach Is Evaluated Based On The Following Metrics
1) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}\frac{|A_t - \tilde{A}_t|}{A_t}$$

Here A_t and $A_t^{\sim}$ represent predicted and actual values.
N represents the number of predicted samples.

2) Regression: Regression is a measure of the similarity between the predicted and actual values. The maximum value of regression is 1 showing complete similarity while the minimum value is 0 representing no similarity.

V. RESULTS

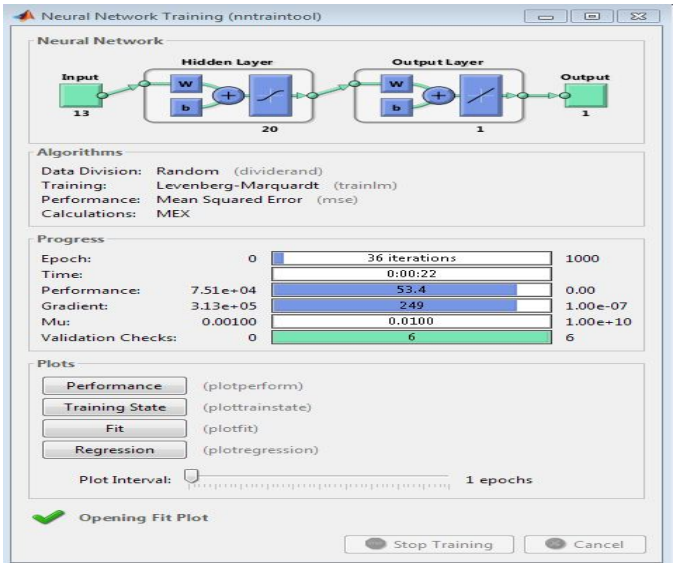

Fig.5 Designed ANN Structure

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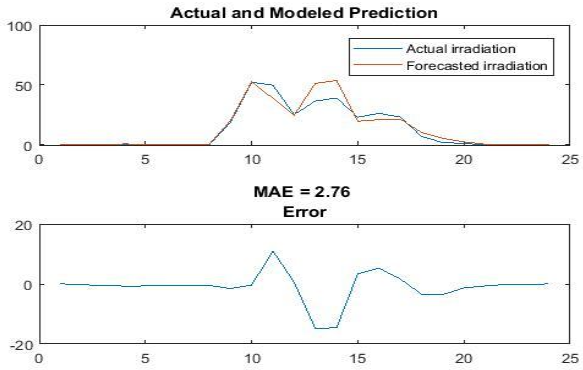

Fig.6 Predicted and Actual Solar Irradiation

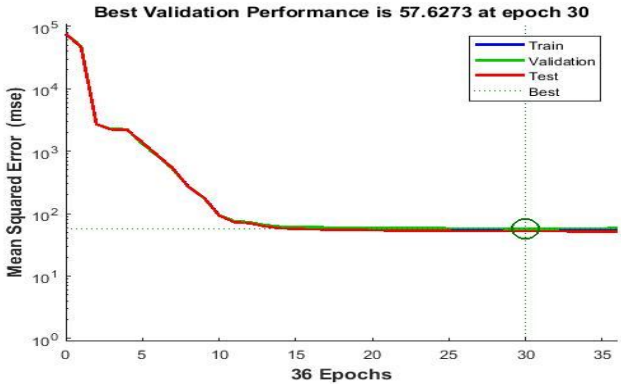

Fig.7 Reduction of MSE with respect to epochs

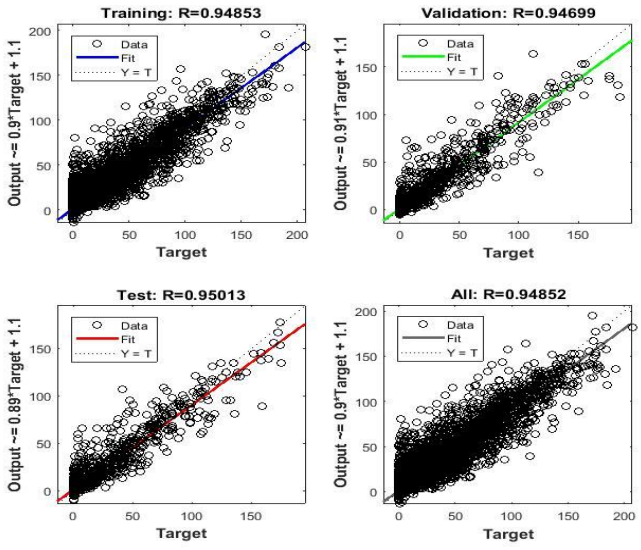

Fig.8 Regression Analysis of proposed system

Figure 5 depicts the designed ANN structure with 20 neurons in the hidden layer. Figure 6 depicts the forecasted and actual solar irradiation. Figure 7 represents the variation of MSE with respect to number of epochs. Figure 8 represents regression which is 0.95 (overall). The MAPE is found to be 2.8 (approx)%.

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VI. CONCLUSION

The proposed approach uses data pre-processing followed by structuring of data to train an artificial neural network that uses the concept of back propagation. The results show that the proposed technique attains a mean absolute percentage error (MAPE) of 2.8% (approx) there by attaining an accuracy of 97.2%. The high accuracy can be thought to be obtained because of the efficacy of the back propagation mechanism. Thus it can be concluded that the proposed approach is an effective technique to forecast solar irradiation which can prove to be instrumental in setting up of large solar power plants thereby migrating vast power consumers from non-renewable to renewable sources of energy.

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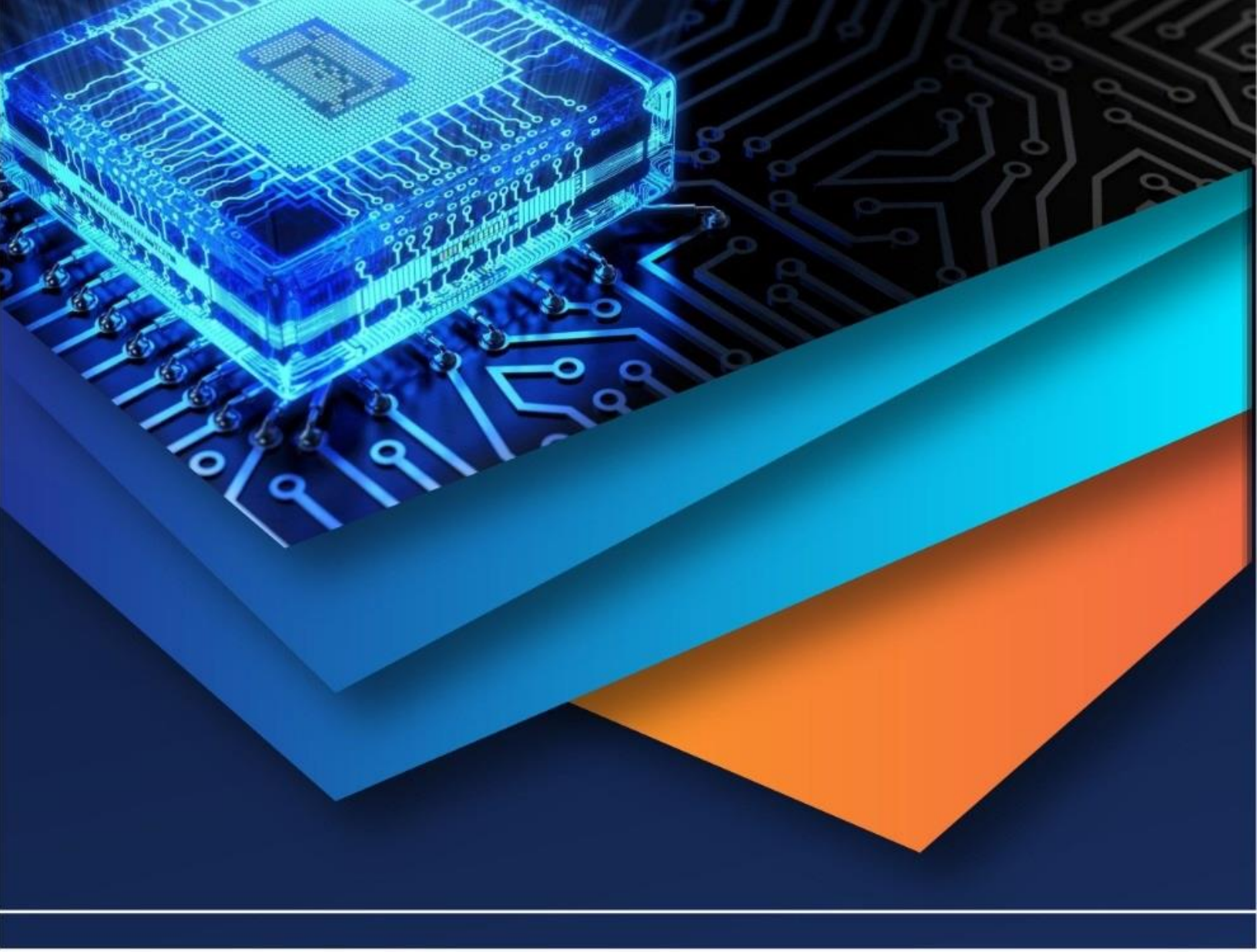

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