iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** VI **Month of publication:** June 2021

DOI: https://doi.org/10.22214/ijraset.2021.35357

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VI Jun 2021- Available at www.ijraset.com

A Gradient Descent Approach for Maximum Power Point Tracking in Solar PV Systems Networks

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Abstract— The intermittent nature of solar irradiation makes it necessary to continuously track the irradiation and change the orientation of the solar panels so as to maximize the PV output. Since the nature of solar irradiation data is both extremely random and complex, hence classical statistical techniques render inaccuracies in the predicted values. Therefore, machine learning based approaches are needed for the estimation or forecasting of the PV output. The proposed approach employs the gradient descent-based approach for attaining the condition of maximum power point tracking (MPPT). The performance of the system has been evaluated in terms of the mean absolute percentage error and accuracy. It has been shown that the proposed system attains an accuracy of 96.31% with an MAPE of 3.69%.

Keywords— Maximum Power Point Tracking (MPPT), machine learning, gradient descent, Mean absolute percentage error, Accuracy.

I. INTRODUCTION

One of the biggest challenges in computing the MPPT is the intermittent and random nature of solar irradiation. Computing the MPPT requires finding the relation among several variables such as time, temperature of solar plate, irradiation, orientation of plate, produced PV power etc. The data to be analysed is generally extremely complex in nature. Due to the above-mentioned reasons, it is extremely challenging to accurately compute the MPPT and estimate the PV output with low MAPE and high Accuracy.

One of the greatest motivations for carrying out this research work on MPPT is the ever-increasing energy demands that have surpassed the consumption of the world. The non- renewable sources are about to deplete as they have been used enormously. Hence the main motivation of this work has been to find newer and better mechanisms to facilitate the harnessing potential of the solar renewable energy. This would help with better research prospects in this highly beneficial area of work. Solar power has to be acquired properly and to its maximum potential that can help in energy management of the world today. The randomness and variations have to dealt with, and a novel approach is to be designed that can predict the local and local solar irradiance with great accuracy. The grid transmission systems cannot be properly planned as a consequence. So to overcome these limitations and use the solar power effectively, there is need for MPPT. The solar thermal power plants use the direct irradiation of solar power to integrate into the conventional primary energy source. But as the solar irradiance is variable in its measure, it becomes inaccurately harnessed. Hence the main aim is to design an effective system to implement MPPT to enhance the effectiveness of PV cells.

II. MATHEMATICAL MODELLING AND CHARACTERISTICS OF SOLAR PV CELLS

A model of PV cell with current source-based circuit is depicted in this section.

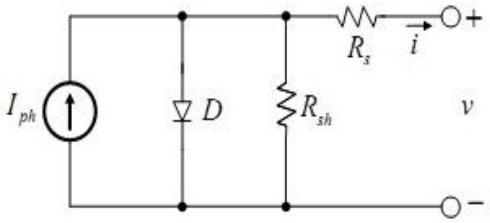

Fig.1 The equivalent circuit of a PV array

Where, R_S denotes array series resistance in Ω,
R_P denotes array parallel resistance in Ω,

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I and V are the output current and voltage of the array in Ampere and Volt.

$$I = N_p \times I_{ph} - N_s \times I_{rs}\left[e^{\left(\frac{q\times V}{A\times K\times T}\right)-1} - \left(\frac{V+I\times R_s}{R_{sh}}\right)\right]$$

Where,

I_{ph} is photo current in Amp,
I_{rs} is saturation current in Amp,
N_S and N_P are the number of series and parallel modules,
q is charge on electron in coulomb,
A is diode ideality factor,
T is cell Temperature with change in irradiation in degree kelvin.

Now,

$$I_{ph} = I_{scr} + K_1 \times (T - T_r) \times S$$

$$I_{rs} = I_{rr} \times \left(\frac{T}{T_r}\right)^3 \times e^{\left(\frac{q\times E_g}{K\times A}\times\left(\frac{1}{T_r}-\frac{1}{T}\right)\right)}$$

Where,

I_{scr} is Short circuit current at reference Temperature in Amp,
I_{rr} is reverse saturation current in Amp,
T_r is reference temperature in Kelvin,
S is solar irradiance in mW/Sq. cm,
K_i is S.C. current Temp. coefficient in (Amp/Kelvin),
K is Boltzmann's constant,
E_g is band gap energy of semiconductor used cell in joules,
Also,

$$E_g = E_{g0} - \left(\frac{\alpha\times T^2}{T+\beta}\right) \times q$$

Where, E_{go} = band gap at 0 kelvin and,

$$V_{oc} = \left(\frac{A\times K\times T}{q}\right) \times \ln\left(\frac{I_{ph}}{I_{rs}}\right)$$

A. Characteristics of PV Cell

Solar PV cells have a nonlinear characteristic where the output is directly dependent on the value of incident solar radiation and cell temperature. By varying the value of this two the output changes which is show in following figure.

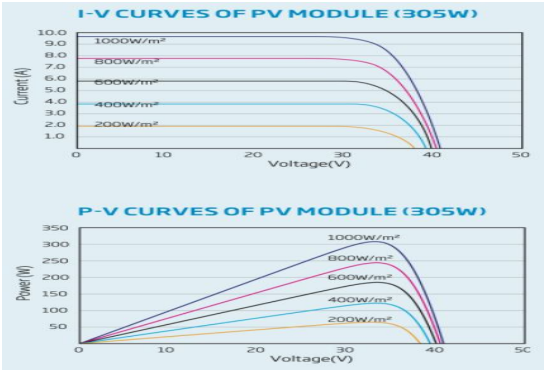

Fig.2 Characteristics of Solar PV Cells

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From above figures it can be clearly seen that output of PV cells is directly proportional to incident solar radiation and inversely to temperature. The maximum power point of any cell is the peak point of above graph whose value changes with radiation and temperature hence a DC-DC converter is used to track that point to give maximum output at any point of time.

B. Existing Challenges

The existing problems and challenges with respect to solar power harvesting and MPPT is enlisted underneath:

1) The set up for the solar power systems and solar panels comes with lots of financial investment and also needs time and effort.
2) There are a lot of variations of solar irradiance depending upon the region of the sunshine and other meteorological factors like the temperature, sunshine intensity etc.
3) The photo voltaic units of the solar systems need to forecast the solar radiation in advance for optimal energy management and planning.
4) The prediction of the solar output power is very useful for planning the proper operation of the power grid systems for managing the solar fluxes optimally.
5) As the solar irradiance from the sun is very fluctuating in nature, it becomes hard to obtain the photo voltaic power and is sometimes erroneous.

III. MACHINE LEARNING BASED SMART OPTIMIZERS

The Machine learning can be crudely understood as the design of automated computational systems which mimic the human behaviour and can be trained in the sense that they can learn from data fed to the system. Primarily machine learning is categorized into three major categories which are:

1) *Unsupervised Learning:* In this approach, the data set is not labelled or categorized prior to training a model. This typically is the most crude form of training wherein the least amount of apriori information is available regarding the data sets.
2) *Supervised Learning:* In this approach, the data is labelled or categorized or clustered prior to the training process. This is typically possible in case the apriori information is available regarding the data set under consideration.
3) *Semi-Supervised Learning:* This approach is a combination of the above mentioned supervised and unsupervised approaches. The data is demarcated in two categories. In one category, some amount of the data is labelled or categorized. This is generally not the larger chunk of the data. In the other category, a larger chunk of data is unlabelled and hence the data is a mixture of both labelled and unlabelled data groups.

Some other allied categories of machine learning are:
Reinforcement Learning
Transfer Learning
Adversarial Learning
Self-Supervised learning etc.

While these learning algorithms can be studied separately, however they are essentially the modified versions of unsupervised, supervised and semi-supervised learning architectures. A more advanced and useful category of machine learning is deep learning which is the design of deep neural nets with multiple hidden layers. The detailed description of these concepts follow.

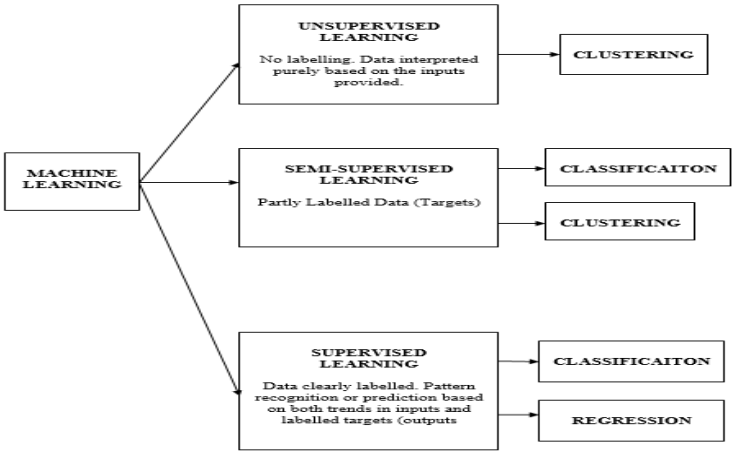

Fig.3 Categories of Machine Learning

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Often, another sub-categorization made is the reinforcement learning which the type of learning in which the aim is to adjust the training parameters so as to maximize the rewards in certain circumstances. They may also possess categorically classified targets prior to training. Typically, some paradigms separate out machine learning and deep learning.
In case of deep learning, the number of hidden layers are multiple and no separate feature extraction is done, and the data is directly fed to the neural network.

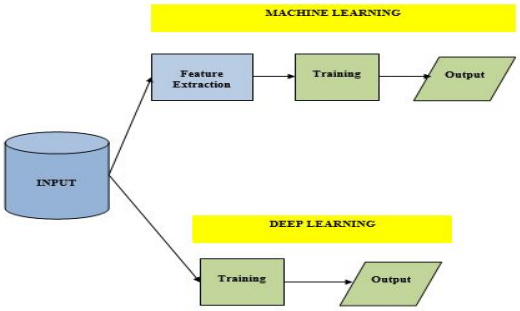

Fig. 4 Machine Learning vs. Deep Learning

IV. MACHINE LEARNING BASED SMART OPTIMIZERS

The gradient descent approach is explained below:
As data is fed to a neural network for pattern recognition, the weights keep updating. However, it has been found that in case of time series problems, the latest data sample have the maximum impact on the latest output. Hence it is logical to calculate a moving average of latest (previous) data and apply it to the neural network [27]. This is also called a moving average. Mathematically,

$$I_k = X_{1,k}, Mean(X)_{k,k-n}, Y_k$$

Here,

I_k is the kth input sample to the neural network

$X_{1,k}$ are the data samples from the first to the kth sample

$Mean(X)_{k,k-n}$ is the mean of the data samples form k-n to k, i.e. it is a moving average depending on the value of k

Y_k is the target

The next step is to implement the back propagation given by:

$$w_{k+1} = w_k - \alpha \frac{\partial e}{\partial w}$$

Here,

w_{k+1} is the weight of the next iteration

w_k is the weight of the present iteration

e is the error

α is the learning rate

$$\frac{\partial e}{\partial w} = \frac{\partial e}{\partial y} \cdot \frac{\partial y}{\partial w}$$

The chain rule in relation (4.6) can be used for computing the error gradient. The gradient descent can be implemented as:

$$p_0 = -g_0$$

Here,

p_0 is the negative of the gradient vector g_0

For the k[th] iteration,

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$$p_k = -g_k + \Theta_k p_{k-1}$$

It is worth noting that the in addition to the weights, the search vector also keeps updating with the iterations. The term Θ_k is calculated as:

$$\Theta_k = \frac{g_k g_k^T}{g_{k-1} g_{k-1}^T}$$

The overall training rule for the algorithm can be mathematically expressed as:

$$w_{k+1} = w_k + \beta_k p_k$$

The essence of the algorithm can be summarized in the following points:

1) The algorithm starts a search for the steepest descent vector right from the first iteration of training
2) The steepest descent ensures fast training
3) Step 2 ensures lower time complexity for the algorithm
4) In addition to the update of weights, the steepest descent vector is also updated with the number of iterations.

The objective function J can be minimized as:
The aim of the approach is to attain the best fit regression line which is equivalent to saying that the co-efficient values θ1 and θ2 , should be adjusted such that to minimize the error between predicted y value (pred) and true y value (y). The cost function J is mathematically defined as:

$$J = \frac{1}{n}\sum_{i=1}^{n}(pred_i - y_i)^2$$

Here,
n is the number of samples
y is the target
pred is the actual output

The data is pre-processed to remove:
Missing values
Infeasible values
Moreover, the data is structured to be fed to the ANN based on gradient descent.
Subsequently, the data is classified into training and testing samples. 80% of the data has been used for training and 20% of the data has been used for testing. The gradient descent approach is utilized for the case. The system performance is evaluated in terms of:
Mean Absolute Percentage Error (MAPE)

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

Here A_t and A_t˜ represent predicted and actual values.
N represents the number of predicted samples.

Accuracy which is computed as:

$$Accuracy = 100 - MAPE\%$$

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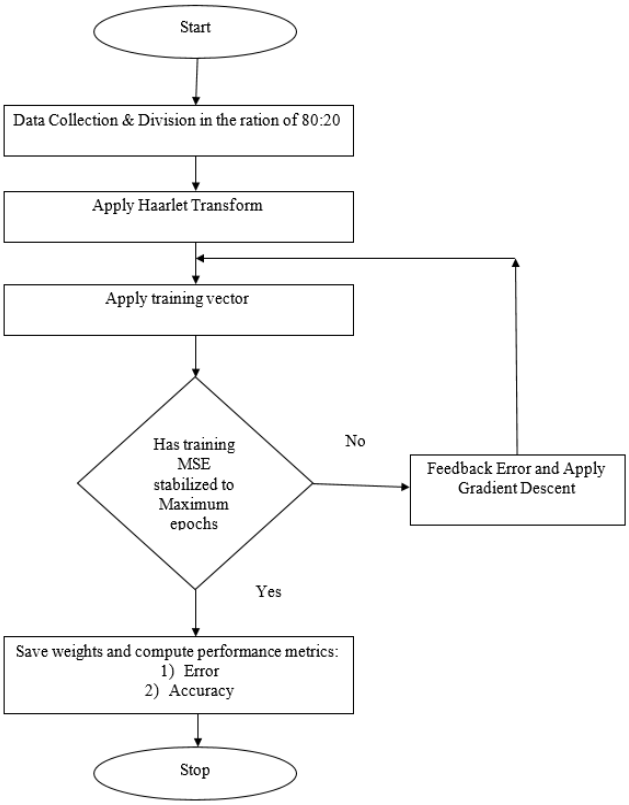

Fig. 5 Flowchart of Proposed System with Gradient Descent

The model has been simulated on MATLAB 2017a primarily due to the availility of standard training alforithms as inbuitt functions. The results obtained are put forth sequentially.

The data utilized is the hourly data of solar PV output with the associated parameters. The data was fetched from the Solar Radiation Lab, ERCOT, University of Texas.

Date	Hour	Temp (F)	RH (%)	PV Output (Kw)
01-01-2019	0	78	82	9
01-01-2019	1	77	91	7
01-01-2019	2	76	94	8
01-01-2019	3	74	97	6
01-01-2019	4	72	100	3
01-01-2019	5	73	100	4
01-01-2019	6	73	100	4
01-01-2019	7	76	97	4
01-01-2019	8	78	91	7
01-01-2019	9	83	74	8
01-01-2019	10	87	63	11
01-01-2019	11	89	55	7
01-01-2019	12	92	49	8
01-01-2019	13	95	43	9
01-01-2019	14	96	40	8
01-01-2019	15	97	38	11
01-01-2019	16	97	36	7
01-01-2019	17	97	33	7
01-01-2019	18	96	37	9

Fig. 6: Dataset Used

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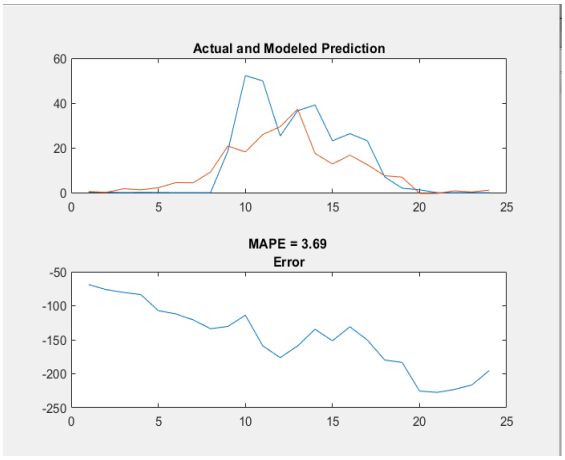

Fig.7 Actual and modelled prediction

The figure above depicts the accuracy with which the neural network is capable to predict future values. The MAPE is found to be 3.69%. Hence the accuracy is 96.31%.

V. CONCLUSIONS

The condition of MPPT is challenging due to the nature of Solar PV output which is extremely complex due to the nature of the irradiation. It can be concluded form the previous discussions that photovoltaic (PV) array is subject to partial shading conditions (PSC), several local maxima appear on the P-V characteristics curve of the PV array which are due to the use of the bypass diodes to avoid hot spots effect. Conventional algorithms can find it difficult to follow the pattern of solar irradiation owing to the fact that solar irradiation varies significantly and some may even become zero during nights. The proposed approach uses a gradient descent based approach for solar MPPT with accuracy of 96.31%.

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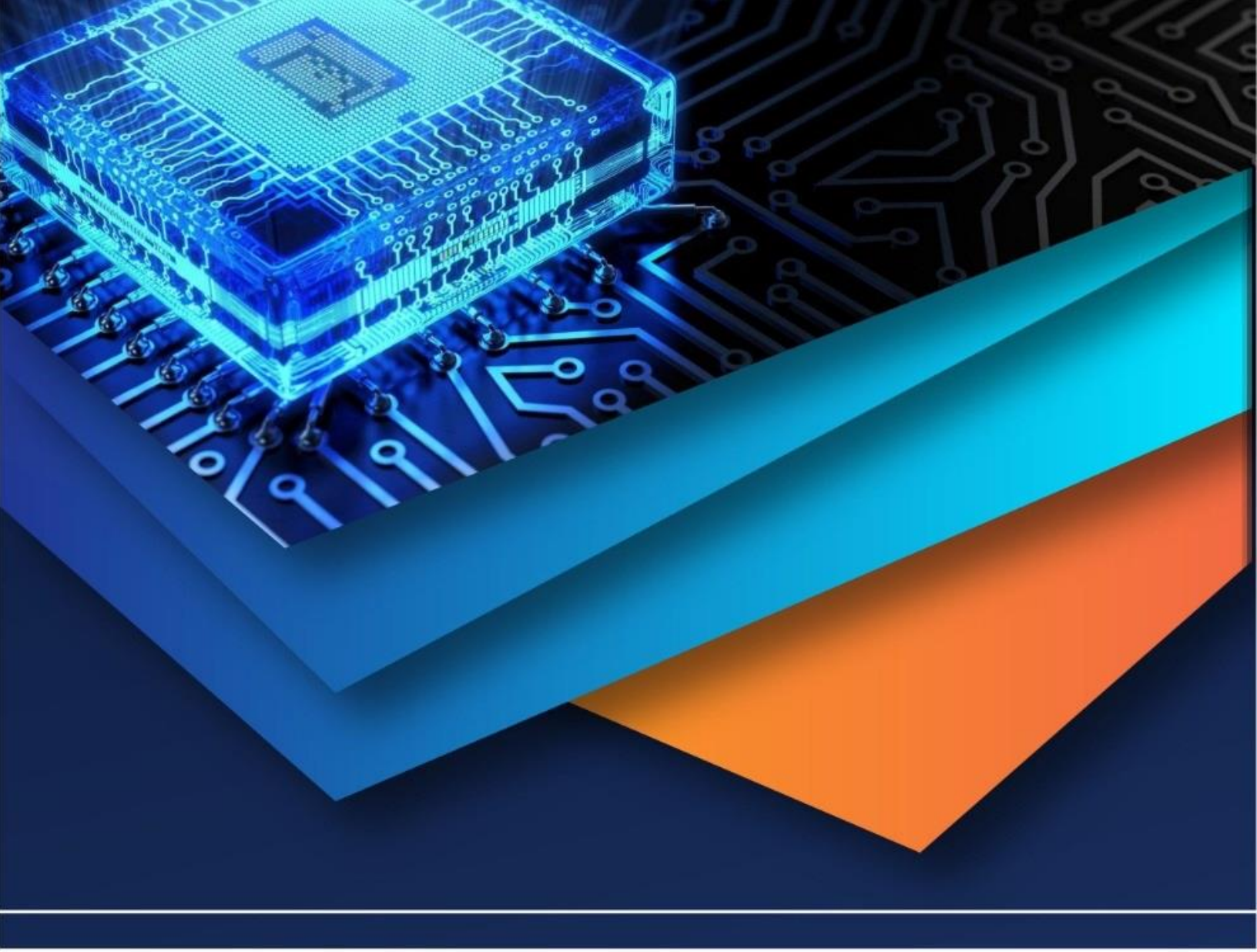

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