iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** IV **Month of publication:** April 2021

DOI: https://doi.org/10.22214/ijraset.2021.33630

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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 IV Apr 2021- Available at www.ijraset.com

Analysis of Mobile Radio Channel Measurements

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Abstract: ***The multipath structure in MIMO can be analysed from dedicated measurements for designing channel models. Many channel measurements have shown that multipath components (MPCs) are distributed as groups known as cluster. Cluster based channel modelling has plays pivotal role in the development of channel model maintaining accuracy simultaneously reducing complexity. For reliable and accurate multipath clustering results are essential. Clustering within wireless channel models assumes that multipath components arrive or depart with similar properties is considered. MIMO performance is also influenced as result of varying inter-cluster and intra-cluster parameters. We have considered a Geometric basedStochastic Channel model (GBSCM) i.e., WINNER. Underthe modelled dataset of C2 WINNER model equivalent to 3GPP Uma, a detailed MIMO setup under Non-Line-of- Sight (NLOS) propagation condition with varying number of clusters and Azimuth Spread of Arrival parameter. The research project is about deriving core parameters for such models. The analysis is concentrated on determining so- called clusters or scatterers, their number and extent. The paper analyses performance of clustering algorithms intheir accuracy and computational speed.***

Index Terms: Azimuth of Arrival/Departure (AoA)/(AoD), Elevation of Arrival/Departure (EoA)/(EoD) Azimuth Spread of Arrival (AsA)

I. INTRODUCTION

Channel modelling has been an important research topicin wireless communications, as the design and performance evaluation of any wireless communication system is based on an accurate channel model. The main goal of channel modelling is to characterize the multipath components (MPCs) in different environments, with a consideration of the tradeoff between model accuracy and complexity. Clustered structure modelling is a kind of modelling methodology, where MPCs are grouped into clusters comprising of both, the intra- cluster parameter domains like Azimuth of Arrival/Departure (AoA)/(AoD), Elevation of Arrival/Departure (EoA)/(EoD) ,delay and inter-cluster parameters like Azimuth Spread of Arrival/Departure (AsA)/(AsD) and Elevation Spread of Ar- rival/Departur e(EsA)/(EsD). The use of clustered structures ismainly motivated by the fact that 3G, 4G, and next-generation systems have larger bandwidth as well as multiple-input- multiple-output (MIMO) arrays are increasing. With the high resolution of MPC on both delay and angle domains, a large body of MIMO measurements has shown that the MPCs are generally distributed in groups, i.e., clustered, in the real- world environments. Therefore, the clustered structure channel models are used to reflect this condition.

Multiple kinds of channel models are proposed and dis- cussed in several publications. They range from ray trac- ing simulations which solve the wave equations for detailed geometrical models of the environment to fully stochastic approaches which rely on the statistics of the received power. A compromise between those two methods is geometry- based stochastic channel models (GBSCMs) which will be considered for this work. They incorporate a stochastic place ment of objects around the Tx and the Rx and perform simplified ray tracing. Well-known GBSCMs are WINNERor COST2100.

II. CLUSTER CONCEPT

An electromagnetic wave which is sent from the transmit antenna through the wireless channel propagates along a num- ber of different paths to the receive antenna(s). Those paths are enabled by objects in the channel through mechanisms like reflection, diffraction or scattering. Collectively, these objects are referred to as scatterers. Figure 1 sketches the multipath propagation between the Tx and the Rx. The different paths are commonly termed MPCs. They can be described by their direction of departure (DoD) and direction of arrival (DoA) which are composed of azimuth and elevation angles in a spherical coordinate system (azimuth and elevation of departure (AoD, EoD) and of arrival (AoA, EoA)). The length of the path is expressed by its propagation delay.

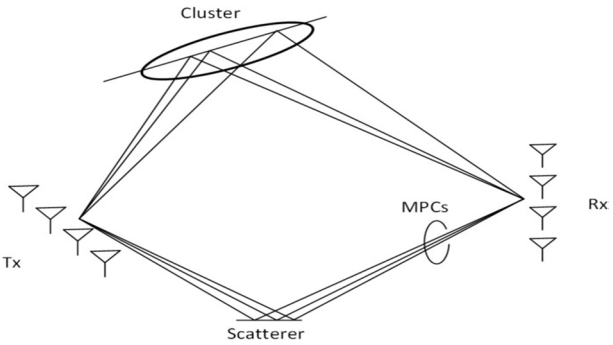

Fig. 1: Multipath Propogation of a MIMO Channel

The exploitation of the multipath richness of a channel leads to so-called multiple-input, multiple-output (MIMO) systems with multiple antennas at the Tx and Rx respectively. On one hand, this increases the reliability of the communication system if diversity techniques are used. Therefore, the receiver

A. Clustering Algorithm

MPCs which are similar in their parameters can be grouped into clusters. The cluster concept combines geometric and stochastic channel descriptions since the cluster centroids are defined geometrically with DOA and DOD but their size is determined stochastically by so-called spreads. Hence, the channel can be described by a few cluster parameters instead of considering each MPC individually. This provides a huge data reduction on one hand and less computational complexity for channel simulations on the other hand. However, an important issue is to define how similar MPCs need to be to belong to one clusters. The cluster spreads are defined as power-weighted standard deviations of the MPCs within one cluster and can be calculated exemplary for the delay domain as :

$$\sigma_\tau = \sqrt{\frac{\sum_{j=1}^{N_c} (\tau_j - \bar{\tau})^2 \cdot P_j^2}{\sum_{j=1}^{N_c} P_j^2}} \qquad (1)$$

which is called delay spread (DS). N_c is the number of MPCs within the considered cluster, τ the path propagation delay and P its power. $\bar{\tau}$ is the mean cluster delay. The azimuth spreads of arrival and departure (ASA, ASD) and the corresponding elevation spreads (ESA, ESD) are found the same way but their periodicity needs to be considered.

Existing clustering algorithms have various drawbacks with respect to complexity, threshold choices, and/or assumptions about prior knowledge. Therefore a reliable and robust cluster- ing algorithm is necessary. We shall be focussing on two such clustering algorithms and try to analyse their performance.

B. Kernel-Power-Density(KPD) based Algorithm for Channel Multipath Components Clustering

A a kernel-power-density (KPD)-based algorithm uses the kernel density of MPCs to incorporate the modeled behavior of MPCs and takes into account the power of the MPCs. Furthermore, the KPD algorithm only considers the K nearest MPCs in the density estimation to better identify the local density variations of MPCs. A heuristic approach of cluster merging is used to improve the performance. The main steps are as follows.

1) Calculating Density : For each MPC sample, say *x*, calculate the density *rho* using the K nearest MPCs as follows:

$$\rho_x = \sum_{y \in K_x} \exp(\alpha_y) \times \exp\left(-\frac{|\tau_x - \tau_y|^2}{(\sigma_\tau)^2}\right) \times \exp\left(-\frac{|\Omega_{T,x} - \Omega_{T,y}|}{\sigma_{\Omega_T}}\right) \times \exp\left(-\frac{|\Omega_{R,x} - \Omega_{R,y}|}{\sigma_{\Omega_R}}\right) \times \exp\left(-\frac{|\Theta_{T,x} - \Theta_{T,y}|}{\sigma_{\Theta_T}}\right) \times \exp\left(-\frac{|\Theta_{R,x} - \Theta_{R,y}|}{\sigma_{\Theta_R}}\right) \qquad (2)$$

where y is an arbitary MPC y /= x. K_x is the set of K nearest MPCs for the MPC x. $\sigma_{(.)}$ is the standard deviation of the MPCs in the domain of (.). In the equation above we use the Gaussian Kernel Density for the delay domain as the physical channels do not favour a certain distribution of delay.

2) *Calculating Density* : For each MPC sample, calculate the relative density ρ_x^* using the K nearest MPC's density, as follows :

$$\rho_x^* = \frac{\rho_x}{\max_{y \in K_x \cup \{x\}} \rho_y} \quad (3)$$

By using the relative density, we normalize the density over different regions, which ensures that different clus-ters have similar level of density, so that it is able to identify the clusters with relatively weak power. It can be seen from above equation that $\rho_x^* \in (0, 1]$.

3) *Searching Key MPCs:* For each MPC x, if $\rho_x^* = 1$, label it as the key MPC $\hat{x}$. We thus obtain the set of key MPCs as follows :

$$\hat{\Phi} := \{x \mid x \in \Phi, \rho_x^* = 1\} \quad (4)$$

The key MPCs can be considered as the initial cluster centroids.

4) *Clustering* : For each non-key MPC x, define its highdensity-neighbouring MPC $\tilde{x}$ as:

$$\tilde{x} := \underset{y \in \Phi, \rho_y > \rho_x}{\arg\min} \; d(x, y) \quad (5)$$

where d represents the Euclidian distance. The high- density-neighbouring MPC allows the non key MPCs toeventually reach a key MPC. Those MPCs which reach the same key MPC are grouped as one cluster.

Both simulation and channel measurements validate the KPD algorithm, and almost no performance degradation is found even with a large number of clusters and large cluster angular spread. The KPD algorithm enables applications in multiple-input-multiple-output channels with no prior knowl- edge about the clusters, such as number and initial locations. It also has a fairly low computational complexity and can be used for cluster based channel modeling.

C. K-Power-Means (KPM) Algorithm for Channel Multipath Component Clustering

The KPM algorithm is based on KMeans algorithm and incorporates the impact of MPC powers. KPM algorithm is widely used e.g. for parametric datasets. The main steps are as follows.

1) Initialize M cluster centroids $\mu_1, \mu_2, \ldots, \mu_M$ randomly, i.e., the M centroid positions are independently chosen as events of equal probability from the data set.

2) Assign each MPC sample x to the reasonable cluster centroid μ_j : for each x, set

$$c^{(e)} := \arg\min_{j} \left(\alpha_x \cdot d_{\mathrm{MPC}}\left(x, \mu_j^{(e)}\right) \right) \quad (6)$$

where superscript (e) represents the (e) -th iteration. C represents the store indices of MPC clustering in the (e)-th iteration. d_{MPC} is the MCD defined by multipath component distance.

3) Update the cluster centroids : for each j, set

$$\mu_j^{(e+1)} = \frac{\sum_{x \in \Phi} 1_{\{c^{(e)} = j\}} \alpha_x \cdot x}{\sum_{x \in \Phi} 1_{\{c^{(e)} = j\}} \alpha_x}$$

4) Repeat steps 2 and 3 until convergence.

The KPM clustering is an unsupervised learning algorithm, and is dependent on an initialization procedure since predefin-ing the number of clusters and their initial positions is critical for this algorithm to work. It is also found that the weight factors of delay and angle domains in d_{MPC} significantly affect the clustering results. Therefore, manual adjustments of algorithm parameters according to different data are usually required to improve the performance, which makes the KPM somehow subjective.

Hence an effective density based initialization algorithm is applied to MPC datasets to estimate a suitable number of clus-ters and their initial positions. The estimated cluster positions are handed to the KPM which performs the assignment of the remaining MPCs to the centroids.

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D. Subtractive Algorithm for Centroid Initialization

This algorithm is a fuzzy solution for the clustering task based on the Mountain algorithm. The algorithm is a den- sity clustering. The 'Subtractive' algorithm is unlinked, and therefore a process to obtain the each cluster centroid, andthe members has to be included in the standard algorithm if needed. Moreover, the probability of each cluster member is reset in order to decrease the cluster duplication error rate of the standard fuzzy classifier.

The algorithm includes three main steps:

1) Calculate the potential of each data point x_i. The poten-tial $P(x_i)$ of x_i is defined as :

$$P(x_i) = \sum_{k=1}^{n} \exp\left(-\frac{4}{r_a^2} \cdot d(x_i, x_k)\right) \qquad (8)$$

2) The SC algorithm selects the data point x_1^* with the highest potential p_1^* as the first cluster center. Then, the potential of each data point is revised by following equation :

$$P(x_i) = P(x_i) - p_1^* \exp\left(-\frac{4}{r_b^2} d(x_i, x_1^*)\right) \qquad (9)$$

where r_b is a positive constant. A good choice for r_b is $1.5r_a$.

3) In this step, the revised potential is maximized. Then, the data point x_2^* with the highest potential is selected as the second cluster center. The process is repeated until a given threshold for the potential is obtained, that is:

$$\frac{p_i^*}{p_1^*} < \delta \qquad (10)$$

The r_a parameter is a factor that affects the performance of resultant positions. If r_a is too small, one big cluster may be partitioned into two clusters, and if r_a is large, two small clusters may form into a cluster. An optimal value of r_a is calculated and used to avoid the error

III. MAIN RESULTS

In order to compare performance of the clustering algorithm methods mentioned we have tried to show the differences using various plots. We have considered dataset WINNER scenario 'C2' under NLOS(non Line of Sight) propogation which is typically Urban Macro Cell. Our datasets have varying number of clusters and varying Azimuth Spread of Arrival. Low ASA value refers less spread in the azimuth plane of the multipath components and high ASA value refers to broader spread in the azimuth plane parameters.

A. Plots and Analysis

For this scenario we have specified number of clusters being4-8 in a dataset of ASA value 2.The dataset comprises of 500 snapshots comprising of 80 MPCs per snapshot and the low ASA values suggest densely packed azimuth parameters.

Since we are regulating the value of Azimuth Spread of Arrival we are primarily focusing on the AoA parameter. For a particular snapshot(22nd) of the dataset comprises of 80multi-path components which are distributed among 4 clusters.From this plot and along other parameter domains like AoD vs Delay, EoD vs Delay, EoA vs Delay it is prominent that the multi-path components are separated clearly in the 4 clusters.We also see Fig 4 showing a 3D plot of AoA versus Delay versus Multipath components that gives a clear picture of the MPCs and how they are clustered in space.

Now we have already the initial guess for the centroids of cluster for the KMean algorithm, while the KPD calculates thecentroids for the clusters based on density of the multi-path components.

As we see from the Fig 4, the KPD algorithm gives an output of 9 clusters while the Kmeans gives an output of 4 clusters. As evident from the input to the clustering algorithm the Multipath components are clearly clustered in 4 sections. KMeans did a better job in judging the final centroid

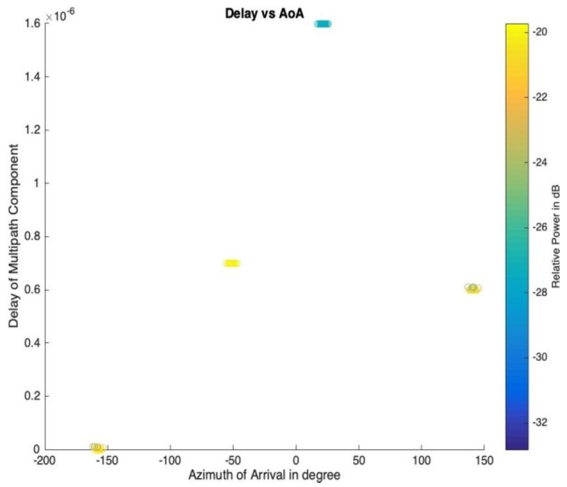

Fig. 2: Figure displays delay vs AoA plot for 80 MPC in asingle snapshot.

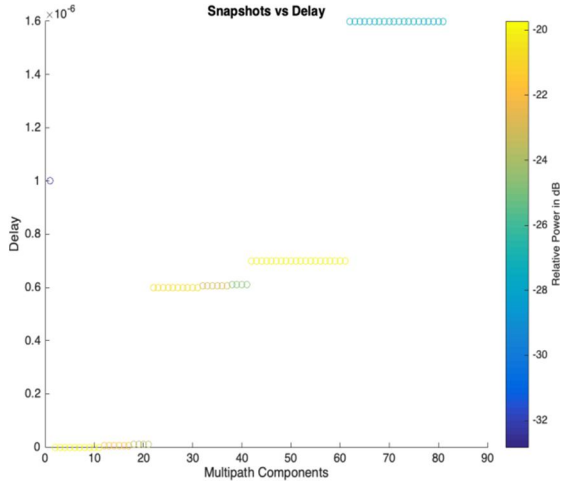

Fig. 3: Figure displays delay vs AoA plot for 80 MPC in asingle snapshot.

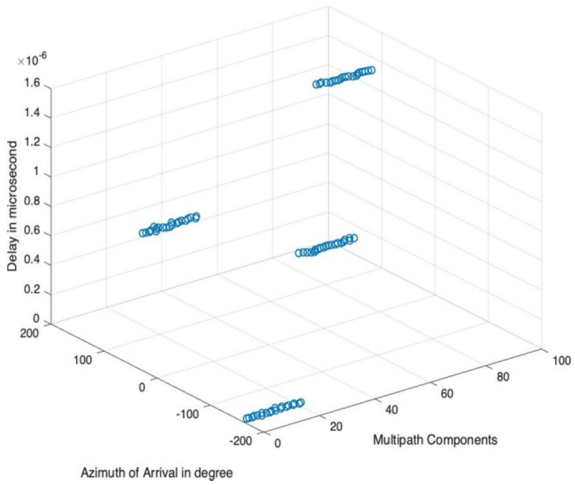

Fig. 4: Figure displays delay vs AoA plot for 80 MPC in asingle snapshot.

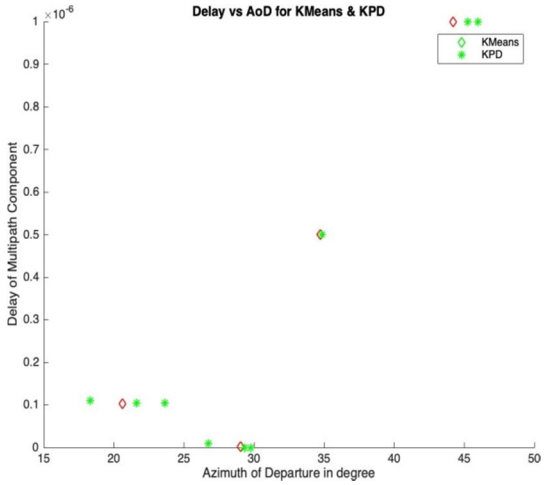

Fig. 5: Figure displays final centroid position from K-Means and KPD algorithm

IV. CONCLUSIONS

This paper presents comparison between different clusteringproposals based on the standards 'K-Means' and 'KPD'. The improved algorithms are thought to be applied in the multi object tracking system described. K-Means shows higher reli- ability when Initial Guess is based on Subtractive algorithm. Although KPD performs better than K-means when K-means have random initial guess for centroid position but Subtractivealgorithm as initial guess for cluster centroids give a far better output. We see multiple snapshots where KPD ends up with farmore than 4 clusters although the initial dataset doesn't suggestso. But the K-means outperforms and successfully clusters the MPCs in required number of cluster centroids. Moreover computational speed for K-means is much better than KPD.

It would be really intuitive to derive further clustering algorithm such that initial guess for the centroid position of cluster canbe determined much more accurately resulting in even better computational speed and accuracy.

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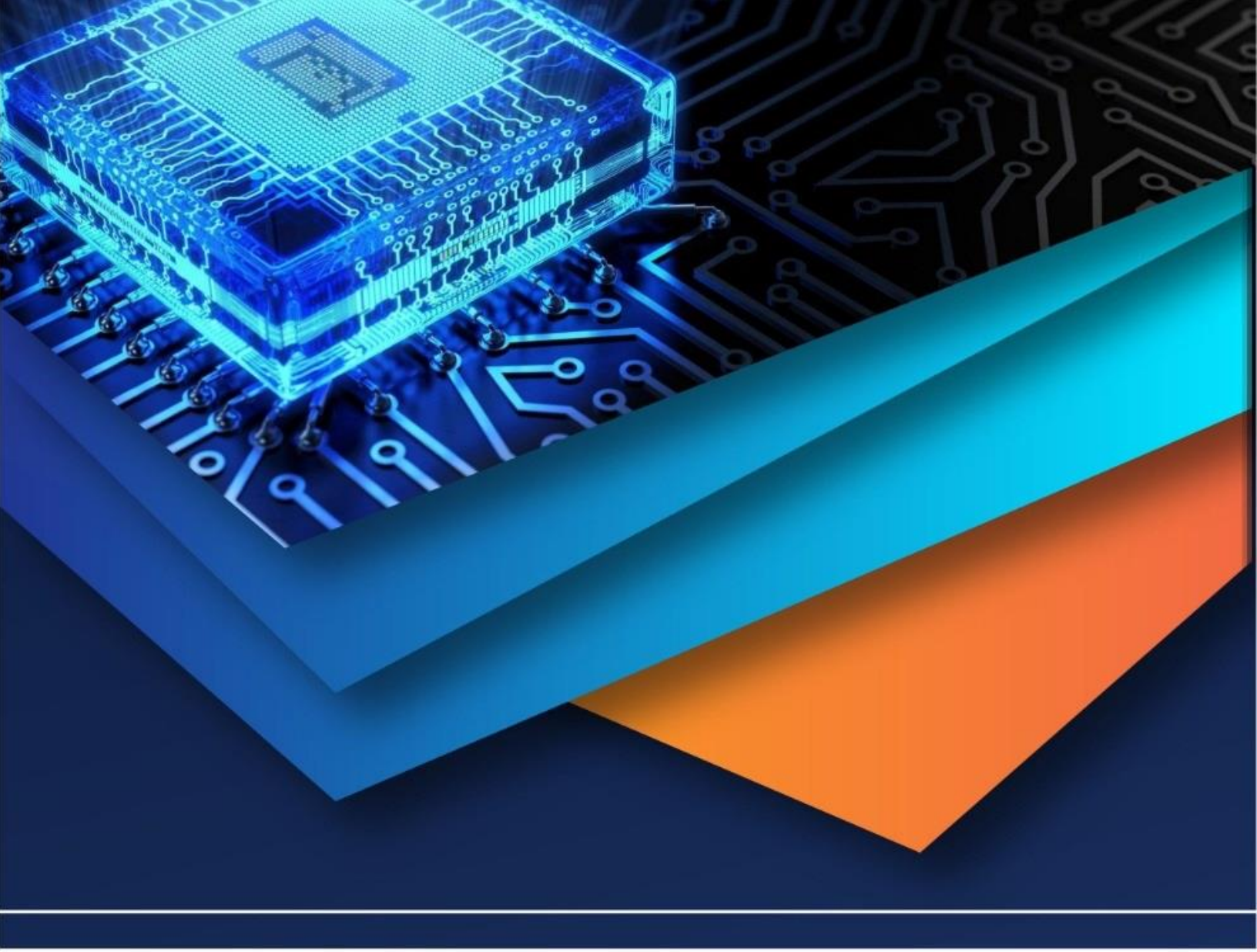

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