iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 8 **Issue:** I **Month of publication:** January 2020

DOI: http://doi.org/10.22214/ijraset.2020.1106

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.177
Volume 8 Issue I, Jan 2020- Available at www.ijraset.com

Change Point Method with Half Logistic Rayleigh Distribution (HLRD)

K. Sai Swathi[1], M. Vijaya Lakshmi[2], G.V. S. R. Anjaneyulu[3]
[1, 2]Research Scholars, [3]Professor, Department of Statistics, Acharya Nagarjuna University, Guntur, Andhra Pradesh, India.

Abstract: The change point model is the new powerful tool to determine whether a change has taken place in the process. It detects the subtle changes frequently missed by control charts. It controls the change wise error rate. In this paper, we analyze the performance of change point approach in case of Half logistic Rayleigh Distribution by considering the Average Run Lengths. It concludes by evaluation of change point model in the context of Half logistic Rayleigh Distribution for detecting small shifts.
Keywords: Control Chart, Average Run Length, Change Point model, Half logistic Rayleigh Distribution.

I. INTRODUCTION

The Statistical Process Control aims to detect and diagnose situations where the process gone out of statistical control. This type of problem involves two aspects namely process and statistical aspects to have detailed outline of some of its statistical modeling aspects see Crowder et al (1987). In fact the status of statistical quality control may be described as one in which the process readings appear to follow a common statistical model. One model is that the process is in SQC, the successive process readings X_i's are independent and sampled from the same distribution. When the process goes out of control, it may behave in different ways. In general we can have two types of causes, those that affect single process readings and then disappear, and the second type of causes or sustainable causes. These causes will continue until they are identified and eliminated. In statistical terminology the isolated causes analogous to an out layer. The Shewart $\bar{X}$ with an R or s-chart is an excellent tool for detecting these special causes, namely isolated or sustainable causes. However Shewart control char is less effective for detecting small changes in the process. Standard tools for detecting sustain changes are the CUSUM and EWMA chart. This chapter focuses on another, less familiar; method aimed at detecting sustained changes is the Change Point formulation when the process averages follow non Normal distribution.

II. CHANGE POINT METHOD

At first let us discuss Change Point Method when the process readings modeled by two Normal Distributions,

$$\left.\begin{array}{l} X_1 \approx N(\mu_1,\sigma_1^2)\ for\ i=1,2.....n, \\ X_1 \approx N(\mu_1,\sigma_2^2)\ for\ i=\tau+1.....n. \end{array}\right\} \qquad (1)$$

Here the number of observations 'n' is fixed in any traditional statistical settings, but this 'n' may increase unlimitedly in phase – II Statistical Process Control settings. Here both settings i.e. Phase-I and Phase-II will be discussed, with context indicating which of the two applies. In the case of in control distribution is N ($\mu_{1,}$ σ_1^2), the readings follows this distribution up to an epoch τ, the change point, at which point they shift to another Normal distribution different in mean i.e. $\mu_1 = \mu_2$, in variability $\sigma_1 = \sigma_2$ or in both mean and variance. In change point method process readings leads to two statistical tasks namely testing task and estimating task. The testing task is to conform whether there has indeed being a change. If the change is there then the task of estimating τ, the time at which shift occurred. Sometimes we may have to estimate some or all of the parameters μ_1, $\mu_{2,}$ σ_1 and σ_2. In all discussions [see Hawkins, 2003] we work on change point has focused on shifts in mean only. i.e. $\mu_1 \neq \mu_2$ but $\sigma_1 = \sigma_2 = \sigma$, throughout this chapter this type of frame work is used here.

From this change point method we have three scenarios based on the amount of process knowledge viz.,

1) All parameters $\mu_{1,}$ $\mu_{2,}$ σ_1 and σ2 are known exactly priory.
2) In control parameters μ and σ are known but μ_2 is unknown.
3) All parameters μ_1, $\mu_{2,}$ σ_1 and σ_2 are unknown.

Throughout our discussions we concentrate on the third scenario namely all parameters are unknown under varying distributions.

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III. IMPLEMENTATION OF CHANGEPOINT METHOD

The formulas below mentioned indicate that the $T_{max,n}$ values are computationally burdensome. For the implementation of the method, construct two arrays of values of

$$S_n = \sum_{i=1}^{n} X_i$$

And

$$W_n = \sum_{i=`}^{n} (X_i - \overline{X}_n)^2$$

There is no need to store the running mean $\bar{X}_n = \frac{S_n}{n}$, but it will be calculated 'on the fly'. The observation of the two new table entries can be calculated from the numerically stable recursions, when a new observation is added

$$S_n = S_{n-1} + X_n$$

And $$W_n = W_{n-1} + \frac{[(n-1)X_n - S_{n-1}]^2}{n(n-1)}$$

The two sample statistic T_{jn} are calculated for every possible split point $1 \le j \le n$ after finding $T_{max,n}$. It is easy and more convenient to find T_{jn}^2. The variance explained by a split at point j can be shown to be

$$E_{jn} = \frac{(nS_j - jS_n)^2}{nj(n-j)}$$

And the analysis of variance identity

$$V_{jn} = W_n - E_{jn}$$

reduces to $$T_{jn}^2 = \frac{(n-2)E_{jn}}{(W_n - E_{jn})}$$

The Change Point test is known by comparing h_n^2 with maximum of statistics of the allowed j values.

If $T_{\max,n}^2 > h_n^2$, leading to the signal of a change point, then it is in significant matter to compute the maximum likelihood estimators

$$\hat{\mu}_1 = \frac{S_j}{j},$$

$$\hat{\mu}_1 = \frac{(S_n - S_j)}{n-j} - \beta^2$$

and

$$\hat{\sigma}^2 = \frac{V_{jn}}{n-2}$$

(the customary variance estimator), using the value j leading to the maximum. The estimators are somewhat biased even though the maximum likelihood estimator are calculated by Hinkley (1970).

The maximizing j is that which maximizes E_{jn}, so the searching step need only to evaluate E_{jn} for each j, making further T_{jn}^2 calculation necessary only for the maximizing E_{jn}. Thus, while at process reading number n there are n-1 calculations to be performed, each involves only about the floating point operations, so even if n were in the tens of thousands calculating $T_{\max,n}^2$ would still be a trivial calculation.

The ever-growing storage requirement for the two tables might be more inconvenient. It is acceptable to restrict the search for change point to the most recent 'ω' instance, if this can be limited along with the size of the resulting search. It is done only when one must keep a table of only the 'ω' most recent S_j and W_j values.

Willsky and Jones (1976) discussed the 'window' approach which is different from above method, in that observations more than w time periods into the past are not lost, since they are summarized in the window's leftmost S and W entry. The lost is the ability to split at these old instants. Appropriate values for the table size W may be in the 500 to 2000 range. It is very large as no interesting structure is lost, but small enough to compute for each new reading to less than 20000 operations.

IV. CHANGEPOINT METHOD WITH HLRD WHEN THE PARAMETERS ARE NOT KNOWN

Consider the model with none of the parameters known; we can test the presence of change point with another general Likelihood ration test. This test is a two sample t-test between before shift and after shift of the sequence, maximized across all possible change points; worsely (1979). For a given change point 'j' where 1≤ j ≤ n-1, let

$$\bar{X}_{jn} = \sum_{i=1}^{j} X_{ij} / j$$

be the mean of the 'j' observations before shift

$$\bar{X}_{jn} = \sum_{i=j+1}^{n} X_{ij} /(n-j)$$

be the mean of the (n-j) observations after shift. The residual sum of squares i.e. Vjn is given by

$$V_{jn} = \sum_{i=1}^{j}(X_i - \bar{X}_j)^2 + \sum_{i=j+1}^{n}(X_i - \bar{X}_j^*)^2 \qquad (2)$$

here we assume that there is a single change point approach at epoch 'j', $\bar{X}_{jn}$ and $\bar{X}^*_{jn}$ are the Maximum Likelihood Estimators of μ_1, μ_2 and $\sigma^2_{jn} = \frac{V_{jn}}{n-2}$ is the usual pooled estimator of σ^2. A conventional two sample t statistic for comparing these two segments could be

$$T_{jn} = \sqrt{\frac{j(n-j)}{n}}\,\frac{\bar{X}_{jn} - \bar{X}^*_{jn}}{\hat{\sigma}_{jn}} \qquad (3)$$

For a stable process, T_{jn} follows at t – distribution with n-2 degrees of freedom. An out of control signal is obtain as soon as

$$T_{\max,n} = \mathrm{Max}\{|T_{jn}|, for 1 \le j \le n-1\} \qquad (4)$$

exceeds some critical value, h_n.

Hawkins et al. (2003) showed that, for any type I error, h_n can be computed by using the Bonferroni inequality. They mentioned that the latter is conservative when a process measurement (n) is large. At same time, they provide empirical control limits, $h_{n,\alpha}$ for different type I error, α, and various number of process observations. Also, for large n values (n≥1), they proposed the following approximation formula for computing $h_{n,\alpha}$

$$h_{n,\alpha} = h_{n,\alpha}\left[0.677 + 0.0191\mathrm{n}(\alpha) + \frac{1-0.1151\mathrm{n}(\alpha)}{n-6}\right] \qquad (5)$$

where ln (.) is the natural log function.

In the case of general change point formulation in which either or both of the parameters μ, σ may shift at the change point τ. Sullivan and Woodall (1996) discuss this formulation and the resultant generalized likely hood ratio test. It provides a single diagnostic to detect shifts in either the mean or the variance or in both. This has the disadvantage of normality assumption. Furthermore, while bounds, approximations and extreme value results are known for the hull distribution of $T_{max,n}$, there is any hardly sample theory for Sullivan and Woodall statistic. Based on these reasons we will consider for the change point formulation to mean the formulation in the third scenario i.e. none of the process parameters is consider known exactly.

In Phase I, with its static set of data $X_1, X_2, \ldots\ldots. X_n$, traditional fixed sample statistical methods are appropriate. So, for example, it is appropriate to calculate $T_{max,n}$ for the whole data set and test it against a suitable fractiles of the null distribution of the test statistic for that value of n. If the analysis indicates a lack of control in the Phase I data set, more data will be gathered after process adjustment until a clean data set is achieved.

Phase II data are the process readings gathered subsequently unlike the fixed set of Phase I, they are from a never-ending stream. As each new reading accrues, the SPC check is re-applied. For this purpose, fixed significance level control limits are not appropriate: rather, concern is with the run lengths, both in-and out-of-control. A convenient summary of the frequency of false alarms is the in-control average run length (ARL), which should be large, and self-contained GLR in which the maximized Likelihood and the Likelihood ratio are used both detection and estimation.

In traditional methods viz., Shewart, CUSUM, EWMA charts, require a Phase I data set to have parameter estimates that can be used in the Phase II calculations. These methods require on to draw a connectional line below the Phase I data and separate the estimated data [Phase I] from the SPC data [Phase II]. On contrast, in change point formulation one does not assume known parameters and hence does not require the estimates produced by a Phase I. Once the preliminaries are complete and the initial process stability has been achieved, the change point allows to go seamlessly into SPC in which, at each instant, all accumulated process readings are analysed and all data is used to test for the presence of a change point. When process remains in control, it also provides on ongoing stream of every improving estimates of the parameters.

The change point model is a schematic approach in which each new observation X_n is added to the data set, the change point statistic $T_{max,n}$ is calculated for the sequence $X_1, X_2, \ldots\ldots. X_n$. If $T_{max,n} > h_n$. Where { h_n is a suitably chosen sequence of control limits, then we conclude that there has been a change in mean. The important point is the choice of the control limits sequence { h_n }. The ideal would be a sequence { h_n }, such that the hazard or alarm rate [the conditional probability of a false alarm at any 'n', given that there was no previous alarm] was a constant α, as in case with the Shewart chart. When the hazard rate is constant the in-control ARL would be $\frac{1}{\alpha}$. This approach was used by Margavio et al. (1995) in the context of an EWMA chart in context known parameters the false alarm changes point over time. Margavio et al. (1995) derived control limits sequence that would fix the false alarm for EWMA chart to a specified value. The present chapter attempts to obtained distribution of $T_{max,n}$. In fact obtaining distribution of $T_{max,n}$ the sequence is far from being able to provide distributional theory sequence. Hence an attempt is made using simulation to tackle this problem.

In fact the change point does not depend on the parameters estimation from Phase I so it is possible to star testing for a change point with the third process reading. Table 1 is obtained by simulation of 10 million sequence of length 200 using HLRD . This table shows the control limits for α value of 0.05, 0.02, 0.01, 0.005, 0.002 and 0.001, corresponding in control ARLs of 20, 50, 100, 200, 500 and 1000 for different 'n' values ranging from 3 to 200.

TABLE 1

CUTOFFS $h_{n,\alpha}$ FOR SAMPLE SIZE 'n' AND HAZARD RATE 'α' STARTING AT SAMPLE 3

n	0.05	0.02	0.01	0.005	0.002	0.001
3	25.292	63.49674	123.321	247.642	624.7742	1216.23
4	8.558804	12.59613	17.68718	24.86927	39.61547	55.91356
5	6.301949	7.863319	9.8749	12.38876	17.23133	21.75909
6	5.514095	6.361373	7.583182	9.015302	11.8205	14.18867
7	5.129309	5.657417	6.54837	7.551386	9.597541	11.20801
8	4.907061	5.258107	5.973179	6.756018	8.42802	9.678984
9	4.765226	5.004638	5.612189	6.263792	7.719035	8.767264
10	4.668586	4.831439	5.366973	5.932352	7.248208	8.168689
11	4.599662	4.706806	5.190913	5.695654	6.915132	7.748683
12	4.548848	4.613635	5.059243	5.519154	6.668356	7.439337
13	4.510447	4.541928	4.957656	5.383133	6.478976	7.202961
14	4.480882	4.485467	4.877333	5.275557	6.329579	7.017067

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15	4.4578	4.440193	4.81256	5.188685	6.209082	6.867457
16	4.439593	4.403347	4.759476	5.117323	6.110113	6.744751
17	4.425129	4.372993	4.715383	5.05786	6.027586	6.642513
18	4.413588	4.347734	4.678344	5.007711	5.957882	6.556188
19	4.404364	4.326538	4.64693	4.964982	5.898362	6.482467
20	4.397002	4.308627	4.620068	4.92825	5.847055	6.418887
22	4.386538	4.280409	4.576892	4.868679	5.763423	6.315113
24	4.380215	4.259692	4.544158	4.822862	5.698551	6.234398
26	4.376777	4.244327	4.518908	4.786917	5.647126	6.17018
28	4.375401	4.232883	4.499178	4.758269	5.605642	6.118144
30	4.375522	4.22438	4.483619	4.73515	5.571698	6.07534
35	4.380065	4.211886	4.457307	4.694134	5.509778	5.996425
40	4.38808	4.207231	4.442486	4.668587	5.469119	5.94358
45	4.397793	4.207093	4.434515	4.652407	5.441458	5.906721
50	4.408296	4.209678	4.43085	4.642231	5.422231	5.880286
60	4.429917	4.219271	4.431035	4.632685	5.399256	5.846687
70	4.451075	4.231638	4.436596	4.631261	5.388276	5.828205
80	4.471185	4.24498	4.44474	4.634106	5.38392	5.818231
90	4.490104	4.258487	4.454119	4.6393	5.383461	5.813384
100	4.50785	4.271779	4.464036	4.64581	5.385391	5.811776
125	4.547614	4.303147	4.48909	4.664533	5.395664	5.815564
150	4.581928	4.331475	4.512962	4.683972	4.909237	5.824669
175	4.611978	4.356974	4.535098	4.702784	4.92368	5.835807
200	4.638651	4.380029	4.555496	4.720569	4.938051	5.847607

It can be noted that from table 1, as the ‘α’ values decreases the control limits $h_{n,\alpha}$ decreases sharply initially, but then stabilizes. Similar type of behaviour can be observed even with Normal distribution; Hawkins (2003).

It may not be reasonable that start testing at the third observation. However there are cases where the process shift occurs at third observation. In practice the particular should gather a modest number of observations to get an initial verification that the Rayleigh distribution was a reasonable fit. Then only the formal change point can be applied. In view of this our main simulation is based on assumption of 9 readings without testing, with testing starting at the 10th observation, however 9 readings itself is hard to believe in a HLRD for the Quality variable. Perhaps it is making reasonable compromise between the conflicting desires.

The same 10 million sequence of length 200 are used to find out cut offs points up to n =200. The resulting control limits are presented in table 2.

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TABLE 2

CUTOFFS $h_{n,\alpha}$ FOR SAMPLE SIZE 'n' AND HAZARD RATE 'α' STARTING AT SAMPLE 10						
n	0.05	0.02	0.01	0.005	0.002	0.001
10	4.575367	5.211797	5.906379	6.486067	7.178893	8.077584
11	4.067423	4.652301	5.288694	5.825742	6.474345	7.307233
12	3.862369	4.400418	4.987548	5.477806	6.064028	6.824088
13	3.715902	4.220501	4.772444	5.229281	5.770945	6.478984
14	3.606051	4.085564	4.611117	5.042886	5.551132	6.220157
15	3.520612	3.980612	4.485639	4.897913	5.380167	6.018846
16	3.452261	3.896651	4.385257	4.781935	5.243395	5.857798
17	3.396337	3.827956	4.303127	4.687043	5.13149	5.726031
18	3.349734	3.77071	4.234685	4.607967	5.038236	5.616225
19	3.3103	3.722271	4.176772	4.541056	4.959329	5.523313
20	3.2765	3.680751	4.127133	4.483704	4.891695	5.443674
22	3.221575	3.613283	4.046469	4.390507	4.781788	5.31426
24	3.178855	3.560807	3.98373	4.318021	4.696306	5.213605
26	3.14468	3.518827	3.933539	4.260031	4.62792	5.13308
28	3.116718	3.484479	3.892474	4.212585	4.571967	5.067197
30	3.093416	3.455856	3.858253	4.173047	4.52534	5.012294
35	3.049223	3.401571	3.793351	4.098061	4.43691	4.908168
40	3.018029	3.363252	3.747537	4.04513	4.374489	4.834667
45	2.994832	3.334758	3.713471	4.005771	4.328073	4.780013
50	2.976908	3.31274	3.687147	3.975357	4.292206	4.73778
60	2.951017	3.280937	3.649124	3.931425	4.240398	4.676777
70	2.933218	3.259072	3.622983	3.901223	4.20478	4.634837
80	2.920229	3.243117	3.603907	3.879183	4.178789	4.604232
90	2.910332	3.23096	3.589373	3.862391	4.158986	4.580915
100	2.902541	3.22139	3.577931	3.849171	4.143397	4.562558
125	2.888793	3.204502	3.55774	3.825843	4.115886	4.530164
150	2.879818	3.193477	3.54456	3.810614	4.097927	4.509018
175	2.873499	3.185715	3.535279	3.799891	4.085282	4.494128
200	2.868808	3.179953	3.52839	3.791932	4.075895	4.483076

V. PERFOMENCE OF THE CHANGEPOINT APPROACH WITH HLRD DISTRIBUTION

The performance of change point approach in the case of HLRD can be assessed with ARL's of both in control and following shift in a mean. This complication does not arise in the case of Shewart or known parameter CUSUM chart. In this case the response to a shift depends on the number of in control observations preceding it. The reason for this dependence is that the non centrality parameter of two sample t statistic depends on the sample sizes. Small values in control period leads to a smaller non centrality parameter and hence low values of shift is considered than a longer in control period.

The above points are illustrated in table 3 by considering α value 0.02, 0.01, 0.005 and 0.002. A shift of size $\delta \in \{0, 0.5, 0.6, 0.75, 1.25, 1.5, 1.75, 2, 2.25, 2.5, 3\}$ was introduced $\tau \in \{10, 25, 50, 100, 250\}$.

The values presented in the table 3 are the ARL's of the change point procedures. These were calculated by simulating a data series, adding the shifts to all X_i's, $i > \tau$ and counting the number of readings from the occurrence of the shift until the chart is signaled. Any sequence which is signaled before time τ was discovered the appropriate formula h_n is used. So that the in control ARL's differs from normal.

Table 3. The arl of the change point procedure when shift occurs at the 'start' position with size 'δ'

α	start	0	0.5	0.6	0.75	1.25	1.5	1.75	2	2.25	2.5	3
0.02	10	3.0392	20.5041	35.9039	103.2116	144.9992	42.0468	20.7980	12.9989	9.2848	7.0770	4.7150
	25	5.324377	20.4541	34.4954	97.95557	134.0896	31.6479	10.04804	10.98858	6.847978	5.47006	2.839615
	50	2.070861	20.3541	31.56612	89.44565	124.332	27.14786	8.980432	9.288579	5.729783	4.450598	11.84368
	100	33.30872	21.2541	28.33235	84.35545	113.312	22.50896	7.080432	5.385795	3.747978	2.77006	1.258894
	250	0.638146	24.7541	22.50036	68.95557	103.3196	18.71959	7.004315	3.245795	2.659978	2.750598	21.96378
0.01	10	3.750405	24.0928	42.1583	121.500	170.1435	49.37897	24.43882	15.25775	11.157980	8.639493	0.977985
	25	3.635815	24.4428	38.50814	110.9017	160.4053	42.06973	15.38824	11.57749	8.634698	5.64493	6.287495
	50	4.439894	23.7428	33.53981	102.4963	149.1053	32.72732	8.623937	10.27493	7.596984	4.6993	2.13432
	100	2.993735	24.2428	28.76814	91.06063	136.0235	26.12732	6.739369	5.57493	5.196984	3.643002	66.93098
	250	7.245406	22.4428	22.50814	78.99627	116.4053	19.46973	5.693686	2.549299	2.219843	3.243002	0.814144
0.005	10	1.269674	27.6815	48.41269	140.6008	196.62105	56.71116	28.0796	17.76664	12.442140	9.82698	2.535413
	25	20479.63	29.1315	42.97927	128.8478	176.4987	47.79157	18.46047	13.16641	9.421419	5.8198	10.77791
	50	0.500191	28.8315	39.1372	123.3685	145.9573	33.39157	11.79605	9.740653	7.464186	3.848002	1.331927
	100	1.017274	29.4315	33.90272	103.5747	119.4042	267.9457	8.396047	8.140653	4.764186	3.5198	32.46803
	250	22.66992	25.9315	26.48204	93.39578	95.95734	17.34567	6.796047	4.740653	2.791858	2.767698	0.893502
0.002	10	0.716479	32.67551	57.28555	163.7121	230.071	67.06878	33.14246	20.75273	14.90403	11.39675	4.355852
	25	5.738785	38.67551	51.76263	143.0114	169.6796	47.20762	22.92455	12.77326	11.29033	8.396752	3.706277
	50	2.014705	39.67551	47.37224	135.7042	130.1663	33.71776	14.74551	7.75326	9.153275	5.217525	5.234484
	100	39.82295	42.67551	42.23632	115.0114	91.13336	23.11776	11.14551	5.725959	6.853275	3.425248	2.721924
	250	0.362897	46.42551	31.66053	95.81359	22.73596	16.44262	7.70512	2.77596	3.702482	2.127481	13.730520

It is clear from the table that the ARL's are affected by the amount of history is gathered before the shift, with a faster response carrying with more history. These ARL's are also depends α and δ. It can also be observed that α is large or δ is large the ARL tends to be smaller, as one would anticipating.

VI. CONCLUSIONS

In the this paper control limits or cut off points [$h_{n,\alpha}$] are obtained by simulation of 10 million sequence of length 200 with the process readings start at 3 and 10 are obtained in the context of HLRD. i.e. when the phenomenon under consideration follows HLRD respectively.

This paper also provides ARL's of the change point procedure obtained by HLRD.

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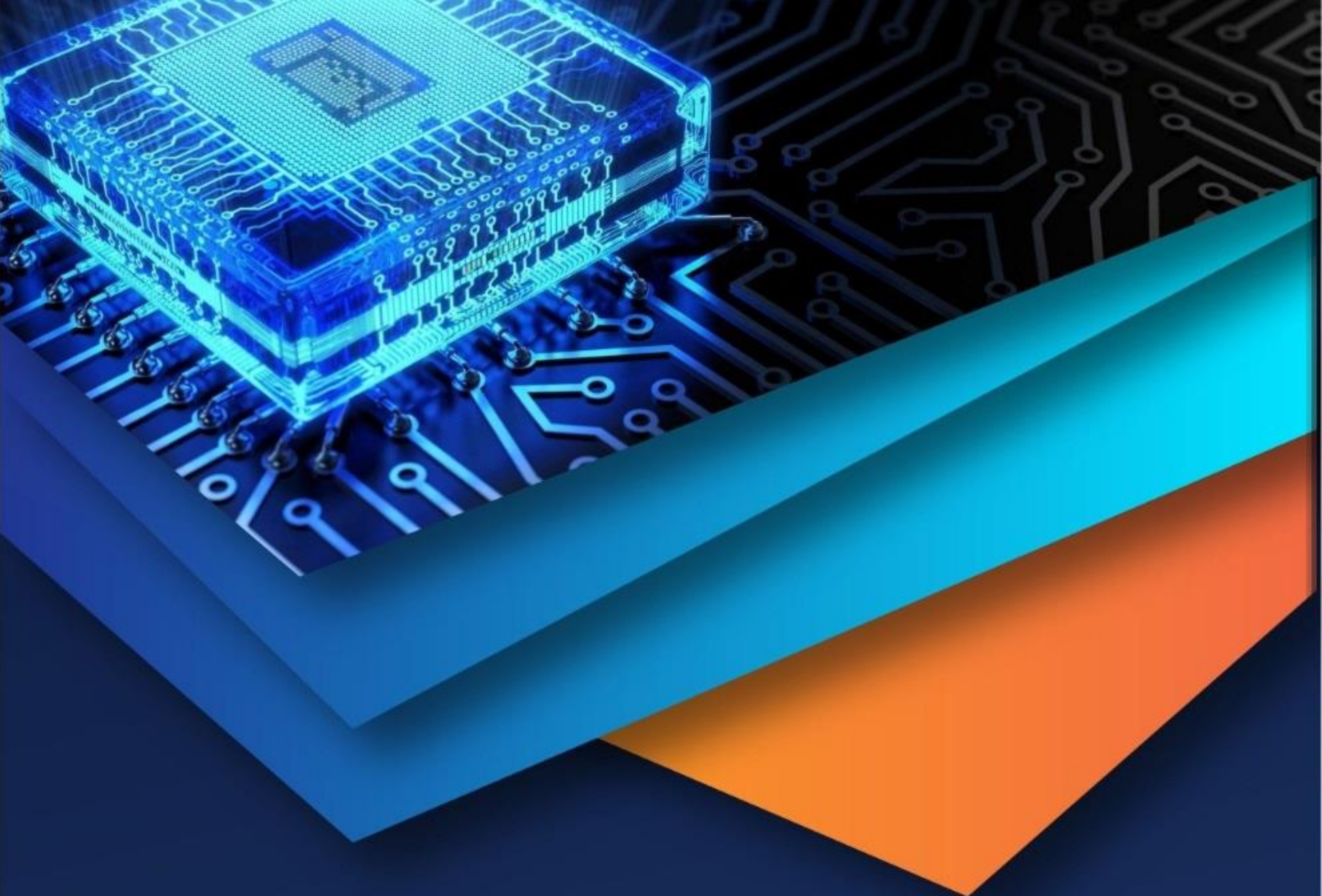

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