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Review Paper on Routing and Networks Using Hybrid AI

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Abstract: In recent years, the engineering and physical sciences have been more interested in traffic dynamics. In order to increase the transportation efficiency of a scale-free network, we propose a routing strategy by building a cost function based on the ratio of degree to closeness centrality. In this brief, we concentrate on the traffic capacity that can be measured by the critical point of phase transition from free flow to congestion. Simulations are used to examine the average route length, traffic load, and maximum node betweenness. To further analyze the traffic distribution, load variance, load mean, and load decrease rate are added. Our approach outperforms the efficient routing (ER) technique by achieving a notable increase in traffic capacity and more equitable load distribution.
Keywords: Complex networks, scale-free networks, traffic capacity, routing strategy.

I. INTRODUCTION

Real networks that are directly relevant to our daily lives include biological networks [3], mobile communication networks [2], and electricity transmission networks [1]. Congestion is a growingly significant and pressing issue as a result of the limited traffic capacity caused by the massive growth in traffic volumes on communication or transportation networks. The question of how to make sure networks can handle increased traffic loads is becoming more and more important. The traffic capacity must be increased in order to reduce congestion. Creating efficient routing plans is one way to increase traffic capacity. Many packets are sent through the hub nodes, which are typically prone to congestion, when using the popular shortest route (SP) routing technique [5, 6, 7]. By transmitting packets via the path with the lowest sum of node degrees, the efficient routing (ER) technique essentially forces the packets to avoid those hub nodes [8].

In a similar vein, Danila et al. considered betweenness in order to reduce the number of hub nodes that appeared on the effective path [9]. In order to determine the best routes, Chen et al. developed the generalized betweenness, which is the betweenness of a route set [10]. Jiang et al. suggested a weighted routing (WR) technique to lessen the high traffic burden of central connections by using the Link betweenness as the weight of each link [11].

Jiang et al. suggested a probability routing (PR) approach, which is more successful than SP and ER techniques, since the waiting probability of packets at a node is proportional to the node's degree [12]. Only the unitary element of static structural features or dynamic information was taken into account by the routing techniques mentioned above. Additionally, some routing systems incorporate both dynamic and static data. In order to efficiently use hub nodes, Wang et al. presented a mixed routing technique based on traffic flow and local structure, which might cause packets to avoid those nodes with high load [13]. By taking into account the waiting time and the shortest path length, Liu and Li established the gravity formula of the transmission path for the packets and introduced the gravitation theory to routing strategy [18], [19]. Furthermore, reinforcement learning (RL)-based routing algorithms have advanced significantly in the last several years. RL-based algorithms may be used to optimize the Network onChip (NoC) routing decision [26].

Traffic capacity has been boosted by earlier routing techniques. More accurate static parameters, on the other hand, can better capture the network structure. We propose an enhanced optimum (IO) routing approach by combining the global static parameter proximity centrality and the local static parameter degree, rather than defining the significance of nodes from a single perspective. In this situation, the nodes' relevance may be more accurately described, allowing packets to more sensibly avoid the hub nodes and increasing the scale-free network's traffic capacity. This is how the remainder of this brief is structured. The models, such as the traffic and network models, are presented in the next section. The IO routing approach is suggested in Section III. In Section IV, the simulation outcomes of the IO and ER strategies are contrasted. Lastly, a summary of the pertinent findings is provided.

II. MODELS

A. Network Model

A BA scale-free network model with two generational traits of growth and preferred attachment was presented by Barabási and Albert [27]. At first, all m0 nodes are linked. The network expands continuously with the addition of a new node at each time step, and the newly added node is connected with m existing nodes with probability $\pi i = \frac{ki}{\sum jkj}$, where ki is the degree of the existing node i and j runs over all existing nodes. A network with N = t + m0 nodes and mt connections is produced after t time steps. When the network scale is sufficiently high, the network tends to be stable, according to the network fixed point theory proof method [28]. Traffic dynamics vary among multilayer network models with various network configurations created by the BA network model and other network models [29].

B. Traffic Model

The network generates R packets with randomly chosen source and destination nodes at each time step. Using the first in, first out (FIFO) principle, each node processes a maximum of one C packet at a time. Packets can be handled in a timely manner when the packet creation rate R is low. The network may function correctly and is in the free phase; packet stacking won't occur. On the other hand, the produced packets that cannot be processed will accrue when R is big enough to surpass the threshold Rc. In this instance, the network is experiencing congestion. The crucial phase transition point is Rc. The transition is described by an order parameter [30].

$$H(R) = \lim_{t \to \infty} \frac{C}{R} \frac{\langle \Delta W \rangle}{\Delta t}, \qquad (1)$$

where W is the amount of additional packets in the network during time t, C is the nodes' delivery capability, R is the packet creation rate, and ‹….› denotes the average across time windows of width t. All of the data packets are processed and H(R) = 0 when R is less than Rc. Congestion will arise and the stable state will be broken when R > Rc.

III. ROUTING STRATEGY

A. Closeness Centrality

A logistics warehouse network must choose a core transfer station that is as near to every other warehouse as feasible. This condition is described by a performance metric called closeness centrality [31], which is utilized to address a variety of issues, including determining the lexicon's word significance [32]. The reciprocal of the average distance to every other node, or closeness centrality, characterizes how difficult it is for a node to reach other nodes. Node I's proximity centrality is described as

(2)

$$CC_i = \frac{N-1}{\sum_{i \neq v} d_{iv}},$$

where div is the shortest path distance between nodes I and V, and N is the size of the network. A node that has a higher proximity centrality is closer to every other node.

B. Routing Strategy

Hub nodes are often the first to experience congestion, which then extends across the whole network. a sensible routing technique that permits packets to select non-hub nodes for transmission in order to balance the traffic load.

In ER strategy, degree is regarded as the cost of the routing function. However, given a global viewpoint, such as proximity centrality, nodes that have the same degree as a local characteristic might not always have the same relevance. As a result, we suggest a novel routing approach that relies on the degree to closeness centrality ratio. The following is its cost function.

$$P_{ij} = min \sum_{n=i}^{j} (k_n / CC_n)^{\alpha}, \qquad (3)$$

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where n traverses every route node. The degree of strategy dependency on the ratio of degree to closeness centrality is characterized by the control parameter α, whereas Pij, kn, and CCn represent the degree and closeness centrality of node n, respectively. Hub node congestion is somewhat reduced when $\alpha > 0$ because packets are more likely to be sent to nodes with a lower degree to proximity centrality ratio. When α is less than zero, the situation is reversed. The approach degenerates into an SP strategy if $\alpha = 0$. The preference for packet selection nodes may be managed by varying the value of α. Additionally, it is possible to determine the ideal control value that allows the network to reach its maximum traffic capacity. The path with the lowest sum of the degree to proximity centrality ratio between source node I and destination node J will be chosen as the packet traffic path. To decide which road to choose, a random integer between 0 and u is created when the cost function values of the u pathways are equal.

IV. SIMULATIONS

A. Indicators for Evaluating Transmission Performance

1) Efficient betweenness centrality [33] is a parameter to characterize the importance of a node which is defined as

$$B_v = \sum_{i \neq j} \frac{\sigma_{ij}(v)}{\sigma_{ij}}, \quad (4)$$

where σij is the number of effective pathways connecting nodes i and j under a certain routing strategy, σij(v) is the number of paths passing via node v among these effective paths, and Bv is the efficient betweenness centrality of node v. In this short, the critical packet generation rate Rc is inversely proportional to Bmax, and all nodes have delivery capabilities set to 1 [34].

2) The average path length is defined as

$$\langle L \rangle = \frac{\sum_{i=1,j=1,i \neq j}^{N} L_{ij}}{N(N-1)}, \quad (5)$$

where Lij represents the path length between node i and j. It represents the average distance of all pairs of nodes. To observe the load situation of ER and IO strategies more intuitively, we introduce three measurement values: load reduction rate, load average, and load variance.

1) Load reduction rate is defined as

$$L_{rr} = \frac{l_{ER} - l_{IO}}{l_{ER}}, \quad (6)$$

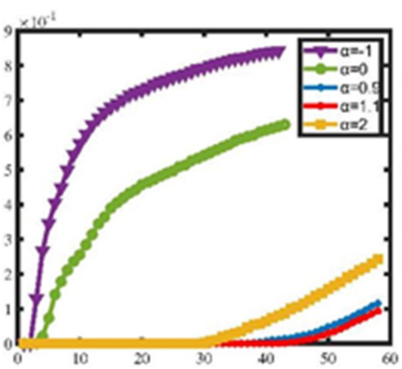


Fig. 1. The relationship between order parameter H(R) and packet generation rate R under different control parameter α with N = 800[5].

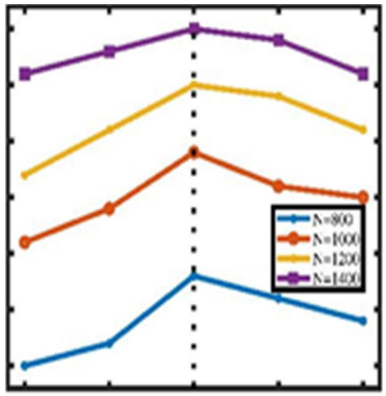


Fig. 2. Traffic capacity Rc with different control parameter α under different network sizes[5].

where l_{ER} and l_{IO} represent the total traffic load under ER and IO strategies, respectively.

2) A set of data fluctuates up and down centered on the average value, reflecting the concentration trend of the set of data. Load average is defined as

$$L_a = \frac{\sum_{i=1}^{N} load_i}{N}, \qquad (7)$$

where N is network size and loadi is the load of node i, that is, the number of packets on node i when the network reaches stability with a fixed R.

3) Load variance is defined as

$$L_v = \frac{\sum_{i=1}^{N} (load_i - L_a)^2}{N}, \qquad (8)$$

where N is network size, loadi is the load of node i and La means load average.

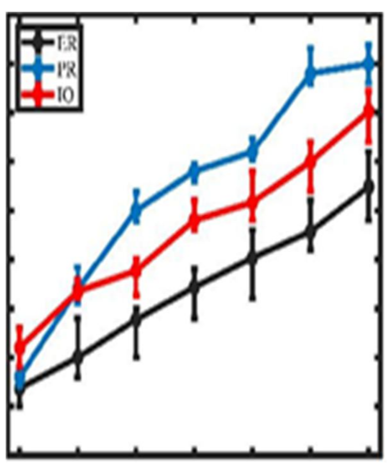


Fig. 3. Traffic capacity Rc of ER, PR and IO strategies under different network sizes[6].

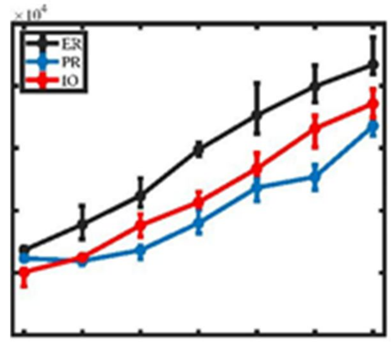


Fig. 4. Maximum node betweenness Bmax of ER, PR and IO strategies under different network sizes[6].

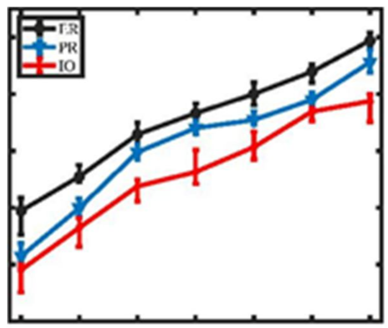
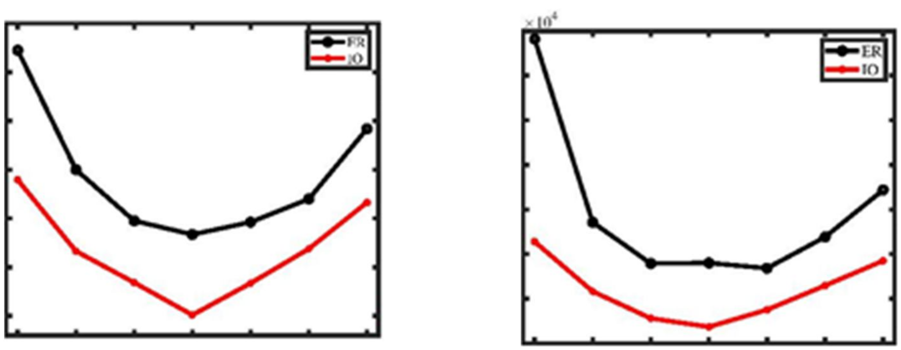


Fig. 5. Average path length <L> of ER, PR and IO strategies under different network sizes[6].

B. Simulation Results and Analysis

MATLAB serves as the simulation tool, and our approach is contrasted with PR and ER tactics. The BA network model is used in all simulations, with m0 = 2, m = 2, and an average degree = 4. The average of over 20 separate networks per network size is used to get the simulation results. Different values of α are used in the experiments. Fig. 1 illustrates the connection between H(R) and R for N = 800. It is shown that Rc reaches its maximum of 43 when α = 1.1. Additionally, as Fig. 2 illustrates, Rc rises initially, then falls with α, reaching its maximum for all network sizes at α = 1.1, indicated by the dotted line. Here, α is referred to as the ideal control parameter. For ER and PR techniques, α = 1.0 is the ideal control value [8], [12]. Additionally, the ER, PR, and IO techniques' respective optimal control parameter values are used to derive all following simulation results.

Figure 3 shows the traffic capacity Rc vs N for the ER, PR, and IO techniques. When N is the same, it is evident that the IO routing method has a higher traffic capacity than the ER approach. The IO method has a higher traffic capacity than the PR strategy when the network size N is less than 800. The traffic capacity of the IO method is reduced when N > 900. Furthermore, when the size of the network increases, the three techniques' traffic capacities improve.



(a) (b)

Fig. 6. (a) Load average of ER and IO strategies under different network sizes. (b) Load variance of ER and IO strategies under different network sizes[5].

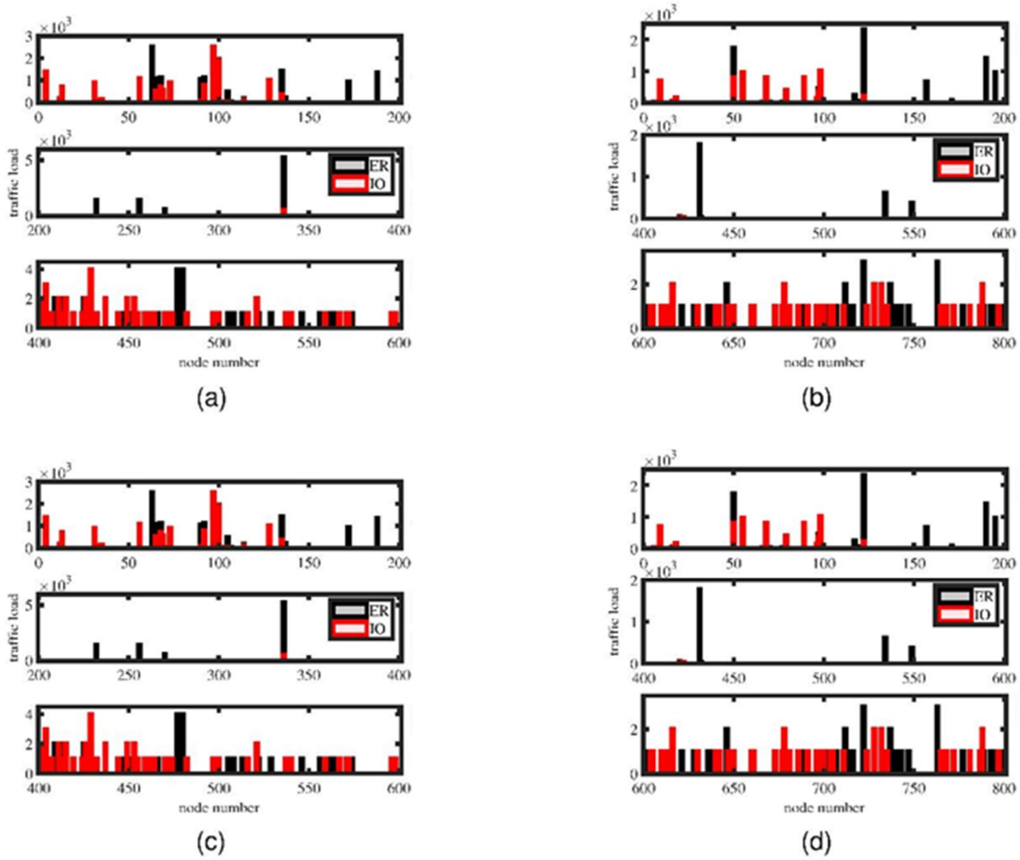


Fig. 7. The distribution of traffic load on nodes under congestion. (a) Network size N = 800. (b) Network size N = 1000. (c) Network size N = 1200. (d) Network size N = 1400[5].

From the optimized behavior of IO strategy relative to ER strategy in Bmax in Fig. 4, we outline that Rc of IO strategy has gained improvement because Bmax is always smaller [34]. The contrast between IO and PR strategies on Bmax and Rc is opposite. When $N \geq 900$, the PR strategy has smaller Bmax.

The average path length is a crucial network parameter. As can be seen in Fig. 5, (L) for the IO routing method is consistently lower than that of the ER and PR strategies, suggesting that, on average, our technique requires fewer hops for packets to reach their destination.

The values of R for the network load study are 50, 55, 60, 60, 70, 70, and 80, respectively, for network sizes of 800, 900, 1000, 1100, 1200, 1300, and 1400. Comparing the IO technique to the ER strategy, the respective load reduction rates are 41.26%, 41.78%, 42.94%, 61.84%, 30.10%, and 31.23%. Fig. 6 presents the load variance and average comparison between ER and IO techniques in a comprehensible manner. It has been noted that our approach significantly lowers the overall burden. Additionally, load average and load variation under IO method are substantially lower than ER strategy, regardless of network size. The traffic load distribution on nodes under ER and IO techniques is displayed in Fig. 7.

We choose representative node groups for each network size using slice windows (every 200 nodes) [35] in order to enhance visualization. We may infer from the previous discussion that the IO method results in a more uniform load distribution and a lower overall load.

V. CONCLUSION

In complicated networks, traffic congestion has led researchers to develop a number of solutions. An efficient route plan is one way to do this. By using degree and closeness centrality, respectively, the network is examined from a local and global viewpoint. We used the two indications to offer an IO routing technique. Regardless of network size, our routing system has a higher critical packet generation rate (Rc) than the ER technique. When network size is modest, our strategy's traffic capacity is superior to that of PR strategies. Regardless of the network size, our strategy's average path length is shorter than that of ER and PR techniques.

Three more indices—load reduction rate, load mean, and load variance—were added to the load distribution diagram of nodes in order to conduct a thorough analysis of the load situation. The outcomes demonstrate that our approach not only lessens the network's overall load but also improves the distribution of that load. Ultimately, simulation results consistently show that the proposed technique has certain advantages in terms of traffic capacity, maximum node betweenness, average path length, and traffic load of scale-free networks.

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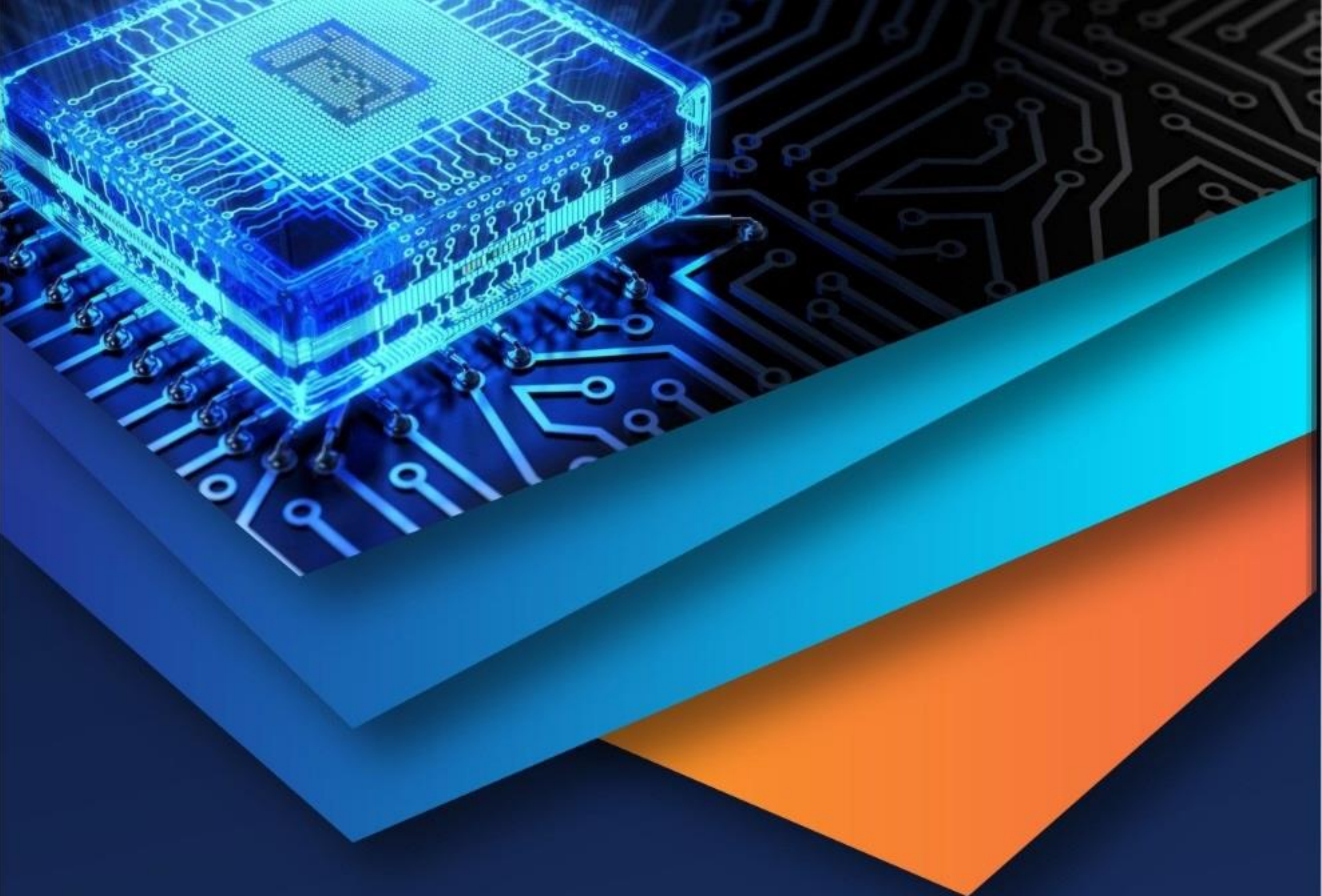

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