iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VI Month of publication: June 2026

DOI: https://doi.org/10.22214/ijraset.2026.83525

A Secure and Containerized Swarm Intelligence Real-Time Energy-Conscious Framework for Automated Fog Nodes Using Hybrid Energy Optimization Algorithms

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Abstract: Cloud computing has revolutionized the way IT infrastructures are implemented, as it is scalable and affordable; however, the rapid growth of cloud infrastructures has resulted in a substantial increase in power consumption of data centers, thus requiring optimization of energy efficiency as a major concern. This study proposes a novel adaptive energy optimization framework aimed at minimizing power consumption of distributed data centers of various cloud infrastructures using Kubernetes for containerization of workloads. The proposed framework utilizes the efficiency of containers to share the operating system kernel of a machine, thus minimizing virtualization overhead. The proposed framework incorporates optimization techniques include Ant Colony Optimization (ACO), Swarm Intelligence, and Dynamic Voltage and Frequency Scaling S (DVFS). The major modules that perform the task include Adaptive Resource Adjustment Algorithm (ARAA) and Automated Resource-Aware Container Lifecycle Management (ARCLM), which together perform the task of resource allocation and automatic termination of idle containers within the Kubernetes environment. The proposed framework also integrates fog computing with cloud computing, enabling the operation of containerized fog computing nodes with the same layer for resource management. The smart contracts operate in both layers, namely cloud and fog, for secure and automated resource allocation, creating it a viable and energy-efficient solution for cloud -fog computing.
Keywords: Fog Computing, Cloud computing, Swarm Intelligence, container, Resource Allocation.

I. INTRODUCTION

The increased development of cloud computing data centres has resulted in an increase in the consumption of energy, which has resulted in the increase of CO2 emissions and environmental concerns. This has resulted in the need to develop more sustainable cloud computing infrastructures. This can be achieved by developing more efficient software level energy optimization, considering the optimization of virtualization, operating systems, applications, and containers [1].Similarly, the development of a hybrid deep learning-based optimization strategy has been presented for the optimization of energy-efficient data migration for heterogeneous cloud environments. This has been achieved through the optimization of containers, virtual machines, and compact yet energy-intensive virtual machines for migration purposes, thus enhancing the efficiency of energy savings as well as minimizing service level agreement breaches compared to existing approaches [7].In addition, containerization has received considerable attention from both the business world as well as the research community. Although it is a highly popular concept, a comprehensive review of the existing research landscape is still lacking. Therefore, recently, a study was conducted to explore the various dimensions of containerization, particularly within a multi-cloud environment, to provide a clearer direction for future research as well as development [8].
Cloud computing has appeared as one of the most sought-after approaches to deliver and manage IT services, and one of the major reasons for its popularity is the flexibility and efficiency it offers. The main advantage of cloud computing is that it can automate resource management and offer a highly efficient and flexible service delivery model [9]. On the basis of the above, it is proposed to use container-aware resource scheduling to address issues of energy and sustainability in the cloud computing. The aim is to minimize the overall energy usage, SLA violation, and CO_2 emission, but without compromising the efficiency of the system and maintaining it within acceptable levels of quality [10].

II. LITERATURE REVIEW

A green container-based consolidation method is proposed to decrease energy usage in cloud data centers handling latency-sensitive applications. The EASY algorithm optimizes energy usage while maintaining service quality, with a small trade-off in response time [11]. In cloud and edge computing systems improving energy effectiveness is more important for building responsible and high performance environment [12]. Energy-efficient resources management is crucial for sustainable cloud operations. To address this issue, a conceptual framework has been developed to efficiently manage large-scale cloud microservices while minimizing response time, energy usage, and carbon emissions [13]. The framework integrates intelligent partitioning, dynamic allocation, resources optimization, and mutation strategies to enhance overall cloud data centers performance [14]. An automated cloud-based framework is developed to improve data centres efficiently by integrating real-time carbon intensity data into intelligent workload scheduling. The approach uses cloud-native and containerized technologies to minimize energy usage and carbon emission while maintaining performance [15].

Cloud computing handles user requests through data center servers, making it suitable for fast and latency-sensitive applications. However, data centers use a large amount of energy, so efficient management and consolidation of container-based services are necessary to reduce power usage while still maintaining good performance for geo-distributed applications [16]. Although cloud computing has become essential in modern society, its rapid expansion has increased energy consumption and caused environmental concerns. To overcome these issues, a learning-based, energy-efficient cloud management approach is introduced to minimize power consumption and carbon emissions without affecting service quality [17]. In addition, a machine learning–based green computing model implemented on AWS helps optimize resource utilization and significantly reduce energy usage. This data-driven approach helps lower the carbon footprint while maintaining efficient cloud operations [18]. An enhanced Kubernetes cluster management approach is introduced that combines ORLE-based leader election with predictive autoscaling. By selecting an efficient leader and proactively adjusting resources according to workload predictions, the approach significantly improves overall cluster performance. As a result, it ensures efficient use of resources while maintaining overall system stability. The model delivers higher throughput, reduced latency, and improved energy and cost efficiency for cloud-based containerized applications [19]. An energy-efficient VM placement strategies to decrease power consumption and carbon emissions in cloud Data Center. The proposed EEVMP and MEEVMP algorithms outperform existing methods by lowering energy usage, SLA violations, and VM migration [20].

In the present era, intelligent devices are interconnected to support a variety of real time applications. These countless IoT devices generate a tremendous amount of data which are subsequently transmitted to cloud for advanced processing and detailed examination. The majority of these operations are time-responsive and must be executed within their specified deadlines [21]. Cloud computing technology has become widely adopted in the modern digital landscape, and its popularity continuous to grow steadily each day. It serves as a platform that delivers a unique pool of resources along with virtualization services to cloud clients. One of the most critical challenges in this domain is the development of an efficient cloud scheduling algorithm[23]. Task allocation represents one of the primary challenges in the cloud computing environment. Effective task allocation is essential to reach cost-efficient execution and to enhance optimal resource usage. The task allocation is classified as a nondeterministic polynomial-time(NP-hard) problem [24]. The most significant conditions within cloud computing framework is job allocation, which plays an important role in determining the overall efficiency of cloud services and offerings . It is the process of assigning the most appropriate cloud resources to a given job or task while taking various factors into consideration, including execution time and cost, framework scalability and reliability, platform availability and throughput, as well as resource usage and schedule length [25].

The machine learning has been developed a Random Forest to schedule jobs in data centers more efficiently, so they use less energy and produce fewer carbon emissions. It highlights future work to further improve resource management by focusing on job level characteristics to make data centers greener [26]. Task allocation in cloud and grid computing is a complex NP- hard problems, and efficient scheduling is crucial to reduce total execution time. It proposes an improving PSO based scheduling method using opposition-based learning, which performs better than existing algorithms in dynamic environments [27].

A hybrid metaheuristic algorithm called (MTOA-GOMVO) to enhance task allocation in dynamic cloud environments. The proposed approach delivers better execution time, higher data rate and improved SLA performance compared to existing method [28].

Hybrid clustering method (H-MVO] that combine Multi-Verse Optimizer with K-means to improve text clustering performance and solution quality. It demonstrates that this hybrid approach achieves better accuracy. Convergence and clustering results compared to traditional optimization and clustering algorithms [29].

Hybrid AWVO-SVM model designed to accurately forecast China's primary energy consumption using key socio-economic factors. It show that this optimized machine learning approach improves prediction accuracy and is used to estimate China's energy demand under different future scenarios [30].

III. METHODOLOGY

This infrastructure is based on cloud and fog computing. It is based on the use of containers for virtualization and smart management of the resources. This process has four main steps. These steps include the creation of cloud containers, the deployment of fog servers, the allocation of the resources, and the management of the fog servers as containers under one orchestration platform.

A. Setting Up Containers in the Cloud

In the cloud, each service is given its own container. This is made possible by the use of Kubernetes. It ensures everything is well organized. The containers are given the privilege of sharing the same OS kernel. This means there is no room for any form of bloat, which is normally found in virtual machines. The containers are not given any hardware. They are given what they need, and they are given it at the time they need it. The Kubernetes platform is responsible for the management of the amount of resources being consumed by the different containers. This ensures the resources are not abused. This means you do not have to keep servers awake for no reason.

B. Deploying Fog Servers

Fog servers are the servers deployed at the edge, the place where low latency is critical. These servers have their own processing, storage, and networking. Fog servers are always aware of the workloads, the energy being consumed, and the resources being utilized. These servers are also connected to the main cloud for any central coordination. The use of fog servers reduces the communication with the big data centre. Only the important data is communicated with the cloud.

C. Dynamic Resource Allocation

Unlike the conventional approach where the allocation of the resources is done beforehand or reserved for a particular task or workload, the allocation is done dynamically depending on the behavior of the workload, utilization patterns, and the power consumption state. This is done through the continuous monitoring of the CPU usage, memory usage, storage usage, and network usage on the cloud and fog systems. When the workload is increased, additional resources are dynamically allocated for the computation. When the workload is low, the dynamically allocated resources are released to prevent power wastage. This allocation is done using the Swarm Intelligence concept and the Ant Colony Optimization (ACO) concept. The ACO concept is based on the behavior of the ants during foraging for food. An ant is considered a task, and the path is considered a node. The nodes with low power consumption, low latency, and high availability are given a higher heuristic value. Over a period of time, the pheromone effect is utilized to train the system with the optimal allocation pattern. This allocation is done considering multiple parameters at the same time, which include execution time, power usage, queue size, and node stability. This is done to avoid the overloading of the nodes and the underutilization of the nodes. This allocation is done dynamically and is a significant improvement over the conventional approach where power is wasted by the over-allocation of the resources. Dynamic Voltage and Frequency Scaling (DVFS) is also utilized along with the above approach. DVFS is utilized for dynamically allocating the CPU frequency depending on the workload.

D. Treating Fog Servers as Containers

Instead of dealing with the fog servers as separate physical entities, the proposed framework treats the fog nodes as container-based entities within the same layer of orchestration as the cloud. In this case, each fog server treats its services as container-based entities and registers with the Kubernetes control plane as a managed node. In this case, the fog servers are no longer treated as separate entities but rather as an integral part of the container-based orchestration layer.By treating the fog servers as container-based entities, the Kubernetes framework treats the cloud and fog resources with the same scheduling and scaling policies. This ensures that there is no heterogeneity in the resource coordination and ensures the flexibility of the system. Workload migration between the cloud and fog servers can be achieved without changing the architecture of the system.

The usage of smart contracts also assists in the improvement of the governance aspect of the hybrid cloud-fog computing system. Smart contracts can be employed for the formulation of pre-specified policy definitions with respect to the allocation of resources, scalability, and power usage. Such smart contracts can check resource allocation requests and ensure that none of the nodes in the network overextend their operation limits. This can enhance transparency and security in distributed decision-making processes.

The usage of containers for fog servers can enhance the compatibility of cloud-native technologies such as microservices, CI/CD, and auto-scaling in the cloud-fog computing model. This can enhance the monitoring, logging, and analysis of metrics in the cloud-fog computing model. Most importantly, the usage of a unified abstraction can enhance security in the cloud-fog computing model.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VI June 2026- Available at www.ijraset.com

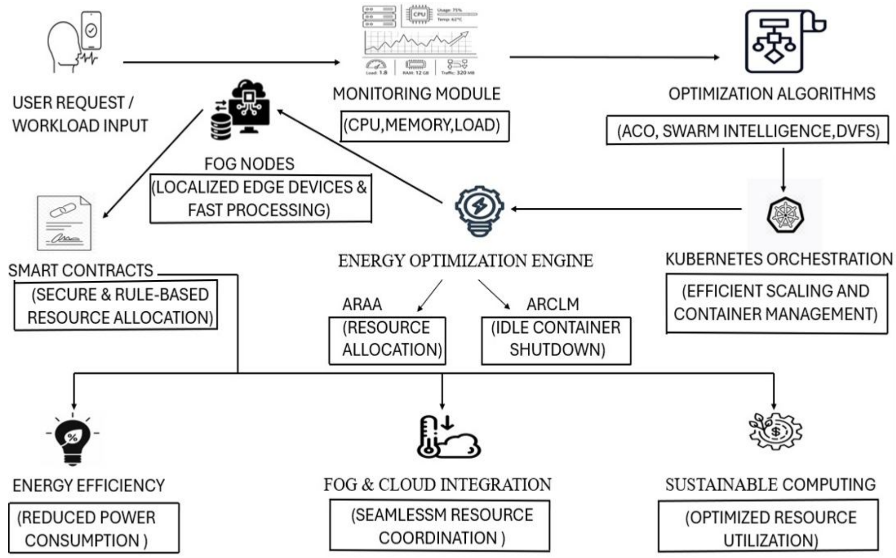

Figure 1. Architecture Diagram for Swarm Intelligence Real-Time Energy-Conscious and Using Hybrid Energy Optimization ARAA & ARCLM.

E. Hybrid Energy Optimization Model Formulation

For the formulation of the total energy consumption for the entire system, the proposed framework uses the following formulation:

$$E_{total}=\sum_{i=1}^{n}(P_{cpu,i}+P_{mem,i}+P_{net,i})$$

Where:

- $P_{cpu,i}$ – CPU power consumed by container i
- $P_{mem,i}$ – Memory usage power
- $P_{net,i}$ – Network transmission power

For the formulation of the processor power, the following equation is used:

$$P_{cpu} = C \times V^2 \times f$$

Where:

- C – Effective switching capacitance
- V – Supply voltage
- f – Operating frequency

As the frequency of the processor increases, the voltage also increases proportionally, so the processor power also increases proportionally, i.e.,

$$P_{cpu} \propto f^3$$

Hence, the frequency of the processor decreases significantly for low workloads, reducing the processor power.

F. Adaptive Resource Adjustment Algorithm (ARAA) – Operational Expansion

ARAA monitors the following parameters:

- CPU utilization
- Memory usage
- Container queue length
- SLA thresholds
- Node energy profile

Let:

$$U_i = \frac{CPU_{used}}{CPU_{allocated}}$$

If:

- $U_i > U_{max} \rightarrow$ Scale Up
- $U_i < U_{min} \rightarrow$ Scale Down

For the formulation of the scaling decision function, the following

$$R_{new} = R_{current} + \alpha(W_{predicted} - W_{current})$$

Where:

- R_{new}= Adjusted resource allocation
- α= Adaptation coefficient
- W= Workload intensity

IV. RESULT AND ANALYSIS

The framework for optimizing energy use for fog and hybrid cloud systems was created and tested using a practical prototype. We used JSP, Servlets and Swing to create the interface layer for the cloud part of the overall system while Swing provided the monitoring and control functionality for the fog servers. We also used MySQL as the database to store all information about workload instances, usage statistics for resources and information related to power consumption. The entire system was deployed in a containerized environment that is managed by Kubernetes, and therefore all of the cloud and fog nodes run as containers.

The evaluation of the system was based on four performance metrics: CPU utilisation, execution time, total system power consumption, and the overall effectiveness of the system to make use of its resources. We applied Dynamic Voltage And Frequency Scaling (DVFS) to manage the processor's power more effectively by actively adjusting the frequency of the CPU according to real time workload conditions as opposed to running the CPU at a constant clock speed. Power usage has been decreased by the reduction of power used because of unused power due to inefficacies from lack of usage or demand for processing capacity. The average CPU utilisation during these conditions was 0.94%, which contributed to the reduction of waste energy.

The best performance in terms of time for workload execution has been realized using Ant Colony Optimization algorithms for workload scheduling compared to all other methodologies tested. ACO has demonstrated superior execution time and greater support for the seamless transitions of workload distribution. Swarm intelligence used in the application of workload balancing across containers, both cloud and fog containers, facilitates removal from the system of bottlenecks and enhances the system's responsiveness. Additional multi-fog servers that were integrated into the system's architecture further enhanced this ability. This all combined with processing data close to its point of origin results in reducing the load placed on networks and in increased time delays.

Moreover, the ARCLM method improved energy efficiency by identifying unused containers and deactivating them (where possible) to achieve additional power savings. Additionally, automated resource allocation based on pre-defined policy frameworks via smart contracts in both the cloud and fog environments further enhanced energy savings. In conclusion, the overall findings of this research indicate that by utilizing a hybrid, container-based cloud-fog architecture will provide more energy efficiency and better utilization of resources than a traditional only cloud architecture.

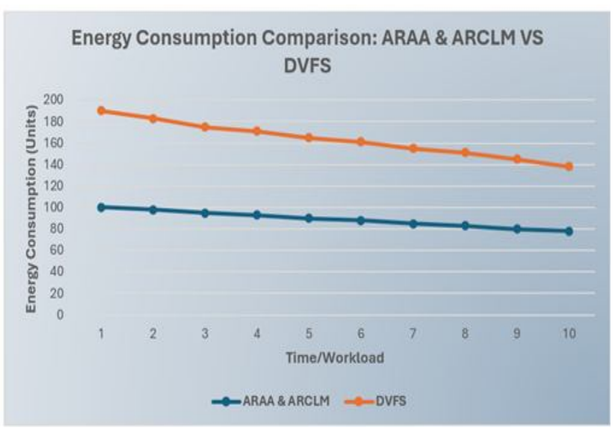

Figure 2. Excess Power Consumption Comparative Analysis: DVFS Vs ARAA & ARCLM

V. CONCLUSION

The research presented in this paper provides an innovative approach to energy-efficient resource management for hybrid cloud-fog computing environments through the implementation of virtual container technology and advanced resource management practices. The deployment of container orchestration using Kubernetes reduces the virtualization overhead of deploying containers to various environments and facilitates the horizontal scaling of applications across both cloud and fog resources. A key component of the framework is the use of optimization techniques, including Ant Colony Optimization, genetic algorithms, and Dynamic Voltage and Frequency Scaling to dynamically schedule workloads, save energy, and optimize the use of resources. The most significant innovation in this work was the integration of containerized applications deployed on fog servers with the orchestration layer of the cloud.

This integration allows for centralized management of distributed resources while maximizing the utilization of those resources. To facilitate the efficient and flexible use of resources, two new algorithms have been developed: an Adaptive Resource Adjustment Algorithm (ARAA) and Automated Resource-Aware Containers Lifecycle Management (ARCLM).

The ARAA dynamically adjusts the allocation of resources while the ARCLM prevents idle resources from being wasted. After conducting experiments with JSP, Servlets, Swing and MySQL to construct and evaluate how well this prototype was built, we have demonstrated that this system functions in real time, has the ability to scale and is a viable platform to deliver applications and provide services. The results of all experiments indicate that the current generation of our framework will decrease the overall amount of energy consumed while improving application performance. This would lead to the development of a strong foundation for the creation of flexible and energy-efficient Cloud-Fog systems, which would promote the use of green computing practices and would lead to sustainable development.

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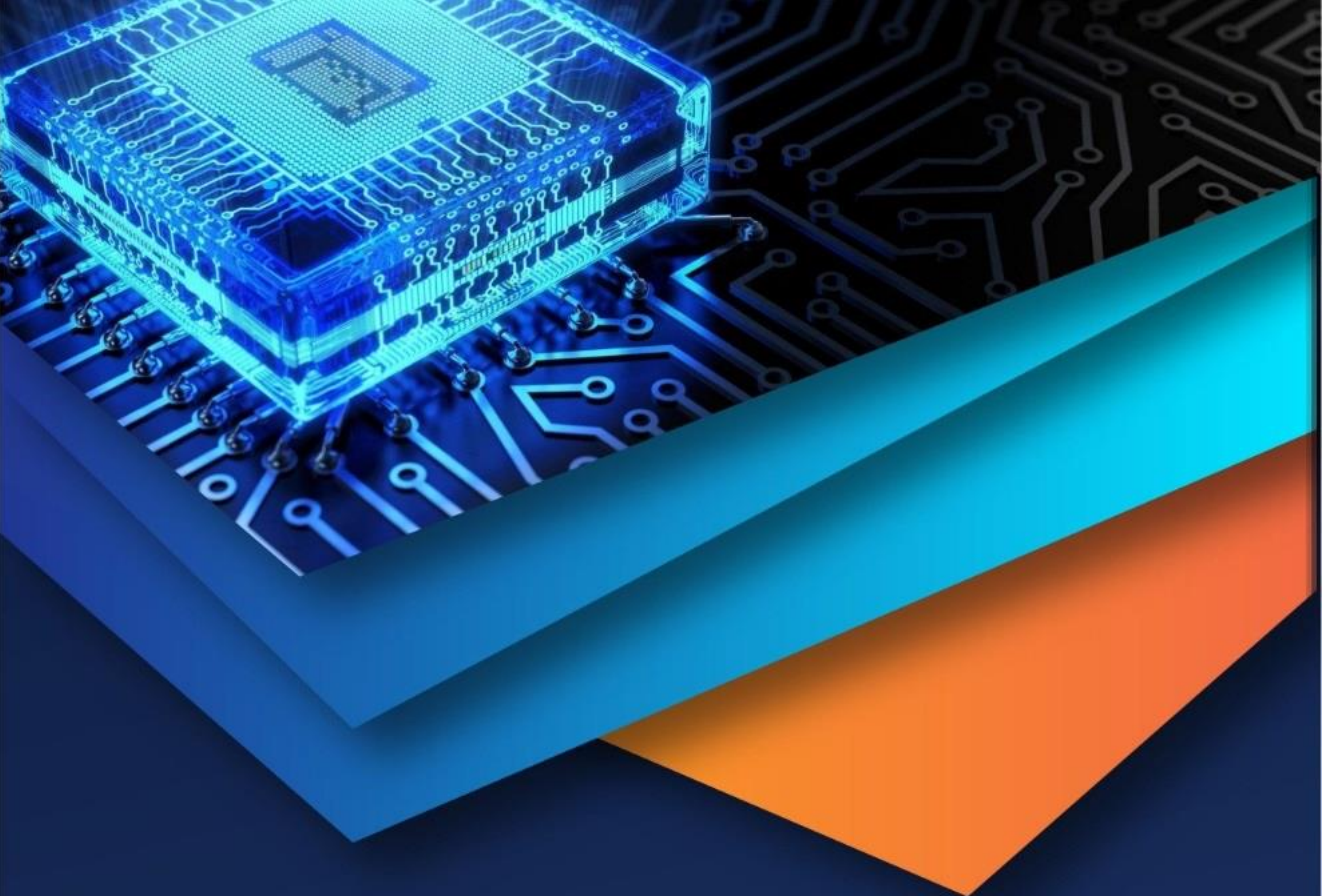

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