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INVESTIGATION OF MULTI-OBJECTIVE CONTAINER SCHEDULING IN CLOUD COMPUTING ENVIRONMENT

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Abstract

Containers have become a preferred virtualization solution in the cloud computing environment in recent years. The challenges of container resource scheduling have progressively become a prominent research topic. Containers are deployed in many new trends such as micro service architecture, edge computing, and server less computing due to their lightweight portability, and security. In order to make better use of containers, examine current placement policies and identify areas where improvements can be done. This survey focuses on various multi-objective optimizations, Particle Swarm Optimization (PSO), and Ant Colony-Optimization (ACO) based scheduling algorithms. This work identifies the various key objectives and basic solutions together with tools and technology. Finally, in order to fully use emerging container technology, this study suggests areas for further research.

Keywords: Virtual Machine; Container; Virtualization; Scheduling; Optimization.

1. INTRODUCTION

Cloud Computing (CC) refers to the provision of computing resources and services, including servers, storage, databases, networking, software, analytics, and intelligence, among others, on an as-needed basis via the internet.

Unlike traditional on-premise data centers, which require the management of hardware installation, operating system, and application installation, network setup, firewall configuration, and data storage setup, among other responsibilities, CC provides an alternative that eliminates the need for these tasks. With CC, a cloud vendor manages the purchase and maintenance of hardware, while also providing a wide selection of software and platform as a service (PaaS) offering that can be leased as needed.

Users are billed for their usage of CC services, making it a cost-effective solution for many businesses. As per the National Institute of Standards and Technology, cloud computing is typically comprised of three service models - Software as a Service, Platform as a Service, and Infrastructure as a Service - as well as four deployment models, including private cloud, public cloud, community cloud, and hybrid cloud.

Additionally, cloud computing possesses five essential characteristics, which are depicted in Figure 1. Virtualization is a key concept in the Cloud Computing (CC) environment. It involves the creation of a virtual instance of a computer system in a separate layer from the actual hardware, allowing for the creation of multiple Virtual Machines (VMs).

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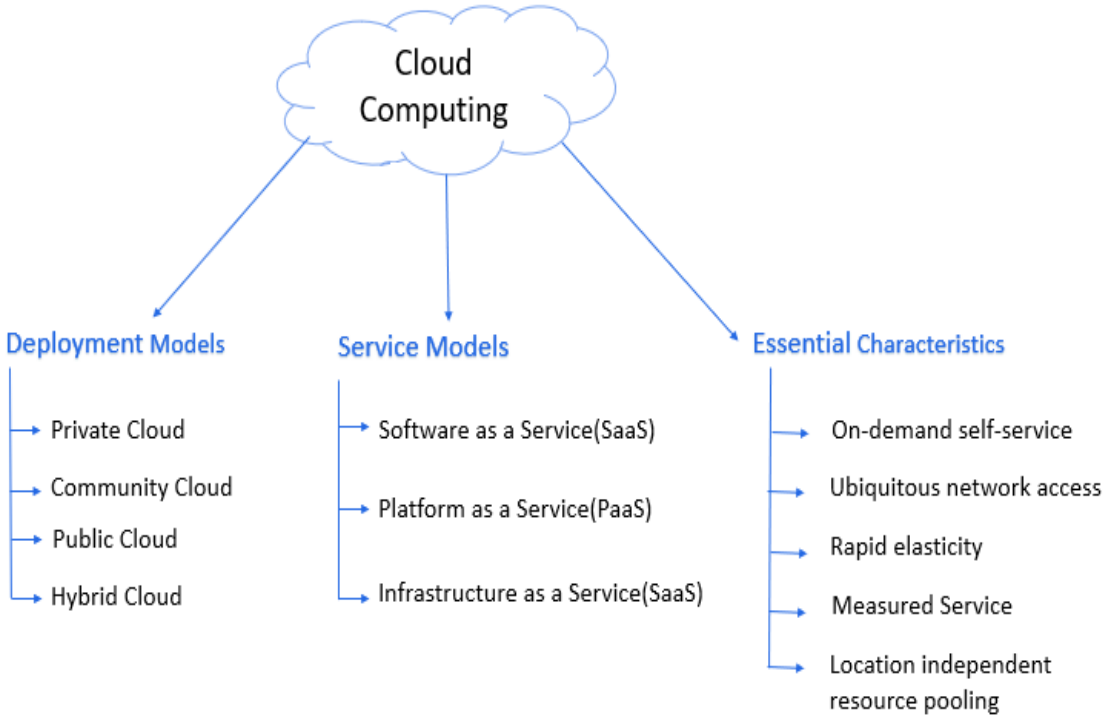

Fig 1: Cloud Computing

Virtual Machines (VMs) are a technology used for creating virtualized computing environments. Unlike a physical machine, a VM cannot directly communicate with the actual hardware. Instead, a thin layer of software known as a hypervisor is required to serve as a communication channel between the VM and the underlying physical hardware. Each VM is allocated a specific amount of computing resources, such as processors, memory, and storage while maintaining separation from other VMs to prevent interference.

Containers are an increasingly popular virtualization solution that has emerged in recent years, gradually replacing traditional Virtual Machines (VMs) [1]. A container is a standardized software component that encapsulates an application's code and all its dependencies to ensure that the application can run quickly and consistently across different computer environments. Virtualization may be handled more easily and quickly using containers [2]. Containerization packages together everything needed to run a single application along with run time libraries. The software program itself, along with all of the code’s dependencies, is all contained within the container. Applications are now able to operate practically everywhere with the help of containers. In parallel, the rise of containerization has introduced a lightweight, agile alternative to traditional virtualization. Containers encapsulate applications and their dependencies in portable units that can run consistently across different environments. Unlike VMs, containers share the host operating system's kernel, significantly reducing overhead and enabling faster startup times.

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Tools like Docker and Kubernetes have revolutionized container management, making it easier to deploy, scale, and orchestrate containerized applications. This shift toward containerization has driven the adoption of cloud-native architectures, facilitating Microservices, DevOps practices, and continuous integration/continuous deployment (CI/CD) pipelines. Beyond virtualization and containerization, the cloud ecosystem has expanded to include server less computing, Function as a Service (FaaS), and Edge Computing, which cater to emerging demands for real-time processing, cost-efficiency, and localized data handling. These innovations are transforming industries, from healthcare to finance, by enabling smarter, faster, and more secure applications. This paper delves into the foundational technologies of cloud computing, focusing on the transition from traditional virtualization to containerization and their respective roles in the cloud ecosystem. It also explores how these technologies address key challenges like scalability, resource optimization, and operational flexibility. Furthermore, the paper highlights emerging trends, such as serverless architectures and edge computing, that are shaping the next phase of cloud computing evolution, solidifying its role as a cornerstone of modern technology.

2. BENEFITS OF CONTAINER OVER VMs

To generate unique and reproducible execution environments for applications, virtual machines (VMs) have been crucial. Containers, on the other hand, allowed users to create customized execution environments in the form of lightweight images rather than VM images.

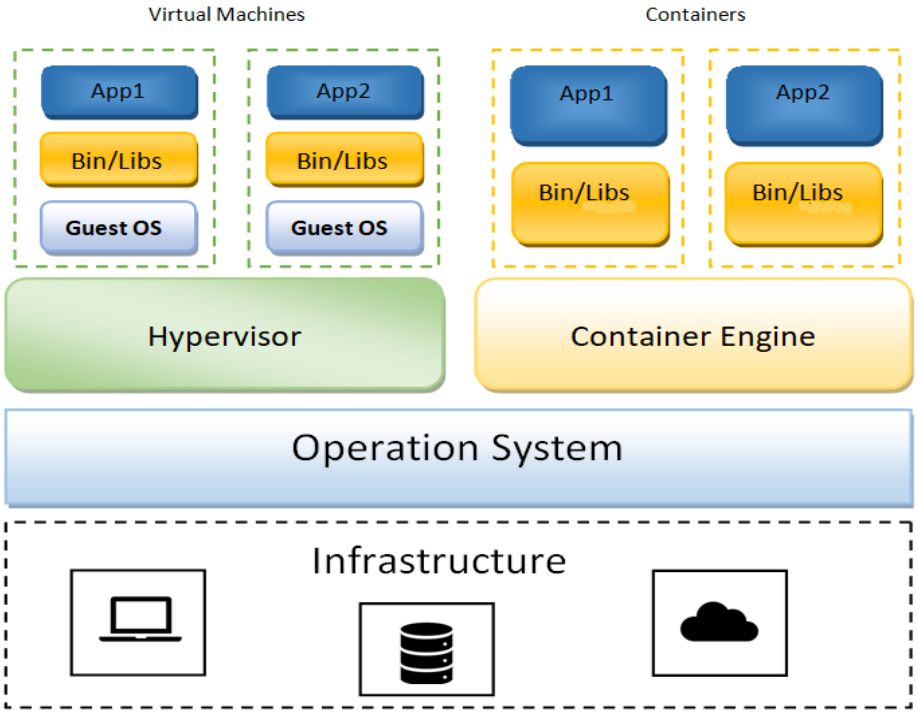

Fig 2: Container vs Virtual Machine

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The container is the better way for micro service architecture and server less computing, to decouple complex applications into several small and independently deployed services.

Virtual Machines (VMs) are commonly used in cloud computing as they enable workloads to be isolated from one another and resource utilization to be managed effectively. However, the additional abstraction layers involved in virtualization can negatively impact task performance, leading to reduced efficiency for customers. As a result, emerging developments in container-based virtualization are making it easier to deploy applications while still allowing for control over the resources allocated to different applications, thereby improving overall performance.

Containers offer several advantages over Virtual Machines (VMs), making them a preferred choice in cloud computing and DevOps environments. Unlike VMs, which require a separate operating system for each instance, containers share the host OS kernel, making them lightweight and efficient. This reduces resource consumption and improves performance. Containers also start much faster, often within milliseconds, compared to VMs, which need time to boot a full OS. Their portability allows applications to run consistently across different environments, minimizing compatibility issues. Additionally, containers enhance scalability, as they can be quickly replicated or removed based on demand. While VMs provide stronger isolation by running independent OS instances, containers still offer sufficient process-level isolation for most applications. They also simplify deployment and continuous integration/continuous deployment (CI/CD) pipelines with tools like Docker and Kubernetes. Furthermore, containers reduce infrastructure costs by optimizing resource utilization and eliminating the need for multiple OS licenses. These benefits make containers a more efficient and cost-effective solution for modern application development and deployment.

Public cloud providers used the capacity to run containers at scale to develop server less computing, in which applications are specified as a collection of event-triggered functions that operate without the need for the user to manually control servers [3]. Latest technological trends like fog computing, edge computing, server less computing, and Microservices are using containers for better performance [4].

3. LITERATURE REVIEW

Container scheduling is a crucial issue that impacts the performance of cloud computing environments. A significant body of literature has revealed the availability of many effective container scheduling algorithms, although there is still room for improvement. Resource optimization objectives are used to measure specific aspects of the solutions generated by these algorithms, which may be single-objective or multi-objective depending on the optimization requirements of the problem at hand. In this context, we are discussing some multi-objective container scheduling algorithms to gain insight into their key concepts, solutions, and potential future directions within the Cloud Computing (CC) environment.

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The author presents a directed container placement method for energy reductions in CaaS cloud systems. Container placement methods are essential in a containerized cloud environment. This paper introduces a new CP policy that drastically lowers power consumption: the DCP method.[5]

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The author presents a directed container placement method for energy reductions in CaaS cloud systems. Container placement methods are essential in a containerized cloud environment. This paper introduces a new CP policy that drastically lowers power consumption: the DCP method.[5]

The author introduced an algorithm that utilized the Whale Optimization Algorithm (WOA) for solving the VM and PM placement problem. Their approach aimed to optimize both power consumption and resource utilization, but it did not address dynamic container placement with minimal migration time and fewer SLA violations in their experiments [5]. Another study utilizing the Whale Optimization Algorithm (WOA) to solve presented a container consolidation scheme that utilized prediction to minimize power consumption while complying with the SLA. This scheme jointly utilized the current and predicted CPU utilization based on the over-utilized and underutilized PMs, but did not consider memory utilization and communication between containers [6]. Additionally, an approach was developed to reduce cloud resource energy consumption, prioritize different users, and optimize makespan under deadline constraints, with experimental results demonstrating good performance [7].

A new container placement strategy was proposed using a Container-VM-PM (CVP) architecture, which employed a fitness function for the selection of VM and PM. This strategy allowed for global observation of resource utilization, making it more effective for resource utilization [8]. Additionally, a PSO-based scheduling algorithm was developed, utilizing the neighborhood division concept to optimize PSO algorithm parameters and generate higher quality solutions. The algorithm considered both response time and load balancing to enhance system performance, and also placed containers with dependencies on neighboring hosts to reduce communication costs [9].

To summarize, the Particle Swarm Optimization (PSO) method is a popular meta-heuristic algorithm used in container scheduling. The LRLBAS algorithm is a PSO-based approach that considers latency, reliability, and load balancing for microservice deployment in edge computing [10].

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The Multiopt algorithm is designed to improve Docker container resource scheduling by considering CPU and memory utilization, network latency, container-node associations, and clustering. However, it may not be effective in handling node failures or overloads [11].

Ant colony optimization is a population-based search method that mimics the behavior of ants in laying pheromone trails to find food. In the context of container-based task placement, a multi-tier scheduler was proposed to optimize resource utilization and minimize the number of active PMs and VMs. However, the architecture only considered the number of CPU cores and memory size as computing resources and did not take into account other resources such as processing cores, storage, and data transfers [12].

Further, an Ant Colony Optimization algorithm is evolved. It considered the number of the physical nodes' failure rates as well as the number of microservice requests, computes resource usage, and storage resource utilization. The pheromone update is ensured using the quality evaluation function, and the selection probability of the best route is increased by combining data from many heuristics. [13]. On the other hand, an ACO-based algorithm has also been prepared. It distributes the application containers over Docker hosts. It is used to balance resource usage and leads to improved performance of applications. The suggested ACO algorithm performs better, and there are a variety of development areas. Application-specific settings might be added to improve the scheduler's performance in every given circumstance. Machine learning techniques will help application containers that make better use of their underlying resources [14].

An algorithm is designed for focusing on different factors that include the pricing model of the acquired resource, the fault-tolerability of the application, and QoS requirements of the running application [15]. In addition, an enhanced container scheduler has been designed to schedule the concurrent container requests on a heterogeneous cluster efficiently with multi-resource constraints. As a result, it performs better container scheduling in terms of resource efficiency and performance. Container dependencies are not considered in this approach [16]. Recent advancements in hybrid scheduling strategies have also been explored, combining multiple meta-heuristic techniques to enhance performance. For example, hybrid PSO-GA algorithms have shown promise in optimizing container placement by leveraging the exploration capabilities of Genetic Algorithms (GA) and the exploitation abilities of PSO. Similarly, Reinforcement Learning (RL)-based approaches are gaining traction for adaptive and dynamic container placement. By training models on real-time workload data, RL-based schedulers can predict and adapt to changing resource demands, reducing SLA violations and improving efficiency.

Future research directions include integrating deep learning models with heuristic algorithms to further refine container placement decisions. Additionally, incorporating blockchain technology for secure and transparent scheduling in multi-tenant cloud environments is an emerging area of interest. The impact of software-defined networking (SDN) on container scheduling is also being studied, as SDN can provide better control over network traffic, reducing latency and improving overall system performance. Moreover, energy-efficient scheduling remains a key focus, with studies exploring novel ways to optimize power usage while maintaining high resource utilization.

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Table 1: Summary of Reviewed Papers

Ref. No.	Objective	Solution	Tool & Technology	Future Work
[5]	1. Reducing power consumption 2. optimizing resource availability	Whale Optimization Algorithm		Optimization objectives, such as 1. High availability 2. Low resource wastage
[5]	1. Power Consumption 2. Resource utilization	A Whale optimization system Humpback whale (encircling, Spiral bubble-net feeding, Searching for prey)	Cloudsim	1. Reducing migration time 2. Eliminating migrated VM 3. SLA violations
[6]	1. Power consumption 2. SLA (Service Level Agreement)	Container consolidation scheme with usage prediction (CNCUP)	ContainerCloudSim	1. Consider communications between containers 2. Memory and network
[7]	1. Minimizing the makespan 2. Energy consumption 3. Resource utilization 4. Deadline Constraints	Energy-Aware Tasks Scheduling with Deadline-constrained (EATSD). Algorithm	Cloudsim	—
[8]	1. Resource utilization	Container, VM, PMPlacement Architecture	Docker Container	1. Container consolidation 2. Load balance
[9]	1. Load balancing 2. System response time	Container scheduling strategy based on neighborhood division in micro service	Cloudsim	Prediction of the timing of container migration
[10]	1. Network latency 2. Reliability of microservice applications 3. Load balancing	LRLBAS algorithm based on PSO (Particle Swarm Optimization) Use the linear weightedsum method.	—	1. Add optimization objectives 2.Comparision with other Algorithms
[11]	1. CPU usage 2. Memory usage 3.Time consumption transmitting images on the network	Multiopt algorithm Score & sort	Docker Container Uses 1. WordPress application with Mysql 2. Apache Benchmark as a stress testing 3. cAdvisor to monitor the status and performance	Fault tolerance of containers ..How to make rapid container migration

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[12]	1. Resource utilization, 2. Minimize instantiated VMs and active PMs	1. Best fit 2. Max fit 3. ACO (Ant Colony Optimization)	1. MATLAB 2. Google cloud Workload	1. Container communication (dependent) 2. Processing core 3. SLA (Service Level Agreement)
[13]	Utilization of computing and storage resources . Number of microservice requests . Failure rate (physical nodes)	ACO Algorithm	Docker container	Reduce the time complexity Consider the other objectives
[14]	Distribution of application containers to the docker host	ACO,Round robin	Docker Container	1.Try another swarm intelligence algorithms for implementing schedulers 2. Machine learning approaches can be useful
[15]	1. Pricing 2. Fault-tolerability 3. QoS	Developa prototype platform	ContainerCloudsim	Estimate the number of resources such as memory and CPU that applications consume
[16]	Scheduling concurrent container requests on heterogeneous clusters	Enhanced Container Scheduler (ECSched)	ExoGeni Kubernetes	1. Problem-Specific Optimization 2. Container Dependencies 3. Resource dynamics

4. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

With the rapid expansion of emerging technologies such as the Internet of Things (IoT), Microservices, autonomous vehicles, and smart infrastructures, containerization has seen widespread adoption within the cloud computing domain. Consequently, the problem of container scheduling has gained significant importance in efficiently managing cloud resources at runtime. A review of existing container scheduling strategies reveals that no single approach can effectively address all critical performance objectives, leaving several open challenges that present key research opportunities.

One promising research direction involves developing security-aware scheduling mechanisms to mitigate security risks associated with deploying containers in cloud environments. Preliminary efforts in this area include the work by Vaucher et al., who utilized Intel Software Guard Extensions (SGX) to establish trusted execution environments [25].

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Similarly, Vhatkar and Bhole incorporated security constraints into the container allocation optimization process. However, further extensive research is required to enhance security aspects in container scheduling [26].

The advent of fog and edge computing has shifted computation and storage closer to end-users, enabling real-time applications while improving energy efficiency, response time, and bandwidth utilization. Critical applications such as 5G networks, IoT services, e-commerce platforms, autonomous vehicles, and content delivery networks rely on this paradigm, with containers serving as a key virtualization technology. Since edge devices have constrained computational power and limited battery life, the development of resource-aware and energy-efficient container scheduling strategies is crucial for these domains. Although initial research efforts have been made (Kaur et al., 2020; Chen et al., 2019; Hu et al., 2019; Luo et al., 2019; Rausch et al., 2021), fog and edge computing remain promising areas for advancing real-time, energy-efficient container scheduling. Specifically, quantum computing-based optimization techniques (Gill et al., 2020) may offer a viable solution for scheduling decisions in fog and edge environments [29].

A review of existing research also indicates that conventional container scheduling heuristics lack adaptive learning components, making them susceptible to performance degradation when faced with unforeseen circumstances. Deep learning approaches could offer robust and adaptive scheduling solutions, though further exploration is required in this direction (Nanda and Hacker, 2018; Lv et al., 2019; Yang et al., 2018; Sung et al., 2019). Machine learning techniques can facilitate workload-specific scheduling policies (Mao et al., 2019) while enabling intelligent predictions for future workloads and resource demands. However, to fully exploit machine learning's potential, extensive historical workload traces covering multiple years are necessary to ensure sufficient data diversity for effective learning models (Kuchnik et al., 2019).

The growing adoption of microservices in various domains stems from their advantages in flexibility, modularity, and scalability. Cloud-native applications often comprise numerous microservices, with their performance being heavily influenced by inter-service communication. This interaction incurs overhead, potentially degrading overall performance (Suo et al., 2018). Consequently, optimizing communication among containers is a critical challenge, leading to the emergence of service meshes (Li et al., 2019), which provide an infrastructure layer for managing service-to-service interactions. Investigating container scheduling strategies that integrate service mesh availability could yield significant improvements in microservice performance.

As containers become a fundamental technology in cloud services, the surging demand for cloud computing has led to escalating energy consumption and operational costs in data centers (Gill and Buyya, 2018). Achieving sustainable cloud operations necessitates the development of multi-objective, holistic container scheduling strategies that consider various data center resources, including networks, memory, processors, cooling systems, and storage (Li et al., 2017; Gill et al., 2019; Townend et al., 2019). Additionally, reducing monetary costs is crucial for big data applications, as excessive expenses can impose a significant financial burden (Chung et al., 2018; Jiang et al., 2019).

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Multi-objective metaheuristic algorithms emerge as promising solutions for holistic management, but their effectiveness can be further enhanced through local search techniques for improved initial population generation. Hybridized algorithms—integrating heuristics with metaheuristics or combining multiple metaheuristic approaches—can refine the optimization search space more efficiently and effectively.

5. CONCLUSION

In recent years, the use of containers for providing cloud services has increased within the cloud computing community. Effective utilization of resources in the cloud computing environments used container scheduling. This work focused on various multi-objective optimization container scheduling algorithms. The survey includes an energy-aware scheduling algorithm with some common optimization objectives such as load balancing, SLA and makespan, etc. The study explored some PSO and ACO-based multi-objective optimization scheduling algorithms. The pricing model, QoS, and concurrent container requests on heterogeneous clusters are also explained in this study. The progression of container technology will create new requirements in the development of a new generation of resource management and scheduling algorithms. The latest technological trends in cloud computing environments like fog computing, edge computing, serverless computing, and microservices offer new possibilities to investigate real-time energy-aware, communication-aware, and security-aware schedulers for these environments. Container scheduling has become extremely important for effective resource utilization in an emerging field. There is room available to improve utilization in the container scheduling area. Mathematical models of multi-criteria decision-making, machine learning, and deep learning may help with load balancing and other decisions that can help to improve container scheduling algorithms.

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