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Efficient Container Scheduling in a Cloud Environments for Resource Allocation

Mr. Shubham Sharma[1], Dr. Ramesh Vishwakarma[2]

[1]*Research Scholar, Department of CS/IT, RNTU, Bhopal*

[2]*Guide, Department of CS/IT, RNTU, Bhopal*

Abstract

Container-based virtualization has emerged as a key enabler of modern cloud computing, offering improved portability, scalability, and resource efficiency. Containers have become the standard unit of deployment in cloud-native environments, leading to widespread adoption of orchestration platforms such as Docker Swarm and Kubernetes. A central challenge in these environments is the efficient placement of containers across a set of heterogeneous nodes while meeting performance, scalability, and availability requirements. Early placement strategies relied heavily on simplistic heuristics, which often ignored vital resource constraints such as CPU and memory. As application workloads diversified, it became evident that multi-resource-aware scheduling, specifically considering both CPU and memory utilization, is critical to maintaining system efficiency and service level agreements (SLAs). This paper presents a comprehensive survey of container placement strategies, focusing on their ability to manage CPU and memory resources effectively. The rapid evolution of cloud computing has underscored the need for scalable and efficient container orchestration. As organizations increasingly adopt containerized applications to achieve agility and portability, the optimization of container scheduling becomes critical for resource utilization, service reliability, and cost efficiency. This research presents an intelligent container scheduling strategy tailored for cloud environments, integrating resource-aware algorithms and real-time performance metrics to allocate containers dynamically. The proposed approach reduces idle resource fragmentation, balances workload across heterogeneous nodes, and adapts to failures through fault-tolerant mechanisms. Experimental analysis using Docker Swarm demonstrates significant improvement in throughput, reduced latency, and enhanced fault recovery compared to traditional scheduling models. The findings highlight the importance of adaptive, context-aware scheduling policies in advancing cloud-native infrastructure efficiency.

Keywords: *Container Scheduling, Cloud Computing, Resource Allocation, Docker Swarm, Fault Tolerance, Load Balancing, Container Orchestration, Scheduling Algorithm, Cloud-Native Applications, Resource Optimization*

I. INTRODUCTION

Container-based virtualization is becoming more popularized in cloud computing, slowly taking over traditional virtual machine-based virtualization. Virtual machine technology and container technology are fundamentally very different. Virtual Machines virtualized the hardware and run a full OS for each instance, which then runs the required application on the system. Containers, on the other hand, run applications directly on the host machine.

Docker containers are widely used as lightweight virtualization tools for building Infrastructure as a Service (IaaS) in cloud computing. Placing containers on machines is a traditional scheduling problem in Docker-based clouds. By default, Docker uses the spread strategy, which aims to place containers across all available machines in docker cluster. But this strategy doesn't account for the actual load on each machine, which can lead to some being overused and others underutilized, ultimately causing inefficient resource use.

Cloud computing is now the go-to for deploying micro services-based applications using lightweight, self-contained containers rather than traditional Virtual Machines. In a micro services setup, applications are broken down into smaller, autonomous, independent parts that are easier to manage and scale in the cloud. This leads to lower maintenance costs and more efficient development as the application grows. To run micro services in the cloud, both hypervisor-based and container-based virtualization can be used. Virtual Machines need an entire OS, which consumes too much CPU, RAM and storage for a quick start. Containers are quicker to deploy micro services, often within microseconds, since they're lightweight, flexible and don't need a separate OS.

Using Docker and Swarm makes it easier to set up multiple servers with custom IaaS or PaaS platforms. Compared to traditional virtualization technologies, Docker offers faster startup speed, lower system overhead, and better resource utilization. But Swarm lacks the ability to manage efficient load balancing and scheduling on its own. So, there's a real need for algorithms that can handle real-time container scheduling and resource load

balancing. In a cloud computing environment, this kind of system would automatically place containers and evenly distribute the load across all machines.

II. Background and Related Work

Container placement strategies have been a significant area of research due to the increasing complexity of cloud computing environments, the growth in containerized applications, and the need for efficient resource utilization. The placement of containers on computing nodes in cloud platforms is crucial for optimizing system performance, maintaining service level agreements (SLAs), and ensuring energy-efficient operation. Early container placement strategies focused on simple heuristics, but as cloud workloads became more heterogeneous, more sophisticated approaches were developed. In this section, we discuss the historical progression of container placement techniques, from basic heuristics to advanced machine learning-based and hybrid approaches. We also analyze the application of energy-aware, SLA-compliant, and multi-resource strategies and examine the limitations of each approach.

2.1 Historical Progression: From Heuristics to Machine Learning

Early research in container placement was primarily concerned with simple heuristic methods, such as round-robin and random allocation. These methods were computationally inexpensive but often resulted in poor resource utilization, as they did not take into account the heterogeneity of workloads or the capacity of individual nodes. These early methods were easy to implement but were limited in their scalability and ability to adapt to dynamic cloud environments.With the advent of cloud computing and the growth of containerized workloads, the need for more intelligent placement strategies became apparent. Researchers began to explore optimization techniques to improve resource allocation. Mixed Integer Linear Programming (MILP) and Constraint Programming (CP) were employed to model container placement as a mathematical optimization problem, aiming to minimize resource wastage while meeting application requirements.

Key Contributions:Initial Heuristic Methods: Early works like [1] and [2] relied on basic placement algorithms such as round-robin and random selection. These methods were fast but inefficient.

Optimization Approaches: MILP-based methods [3], [4] provided mathematically rigorous solutions, though at the cost of scalability and real-time performance.

As workloads in cloud environments became more diverse and dynamic, it became clear that simple heuristics and optimization techniques were insufficient to address the complex challenges in container placement. This led to the exploration of machine learning (ML) models, which could learn from historical usage data and adapt placement decisions based on workload patterns.

2.2 Heuristic-Based Methods

Heuristic-based methods for container placement are generally based on rule-of-thumb algorithms that focus on minimizing computational cost and ensuring simplicity. These methods do not rely on mathematical optimization but instead use predefined rules to determine the placement of containers. While these methods are fast and easy to implement, they often fail to produce optimal solutions, especially in heterogeneous environments where CPU and memory utilization need to be considered jointly.

One of the most widely used heuristic algorithms for container placement is the bin-packing algorithm. This algorithm places containers into available nodes based on resource requirements, such as CPU and memory, while attempting to minimize wasted resources. However, it often struggles with balancing resource utilization across nodes and fails to adapt to dynamic changes in workload.

Key Studies:

Bin Packing Algorithms: Early research such as [5] and [6] applied bin-packing principles to allocate containers to nodes. These methods often led to resource imbalances and underutilization.

Round Robin and Random Placement: The methods in [7] and [8] examined simple round-robin and random placement algorithms, which demonstrated poor performance when scaling.

Despite their limitations, heuristic-based methods remain valuable for their simplicity and low computational overhead, especially in small-scale cloud deployments.

2.3 Optimization-Based Approaches

Optimization-based techniques for container placement aim to find the optimal solution by formulating the placement problem as an optimization task. These techniques often utilize Mixed Integer Linear Programming (MILP), Constraint Programming (CP), and other mathematical methods to find the best allocation of containers on nodes while satisfying resource constraints (e.g., CPU, memory, and network bandwidth). Optimization approaches can provide optimal or near-optimal solutions but often suffer from high computational complexity, making them impractical for real-time container placement in large-scale cloud environments.

Key Studies:

MILP for Container Placement: Studies such as [9] and [10] have used MILP to model the container placement problem. These approaches generate optimal solutions but are not scalable to large cloud environments due to their high computational overhead.
Constraint Programming (CP): Researchers in [11] explored CP as an alternative to MILP, focusing on constraints such as resource requirements and node availability. However, CP-based approaches also face scalability challenges in large clusters.
Optimization-based methods are highly effective in small to medium-sized deployments where finding an optimal solution is more feasible. However, for large-scale cloud environments, the computational overhead often makes these methods less suitable for real-time applications.

2.4 Machine Learning-Based Methods

Machine learning (ML) has gained significant attention in recent years as a way to improve container placement in cloud environments. ML models can learn from historical workload data and make placement decisions based on observed patterns. The most promising ML approaches are supervised learning, unsupervised learning, and reinforcement learning (RL). These methods can dynamically adapt to changes in the workload, making them ideal for cloud environments where workloads can be highly variable.
Reinforcement learning (RL), in particular, has shown promise in container placement due to its ability to learn optimal placement policies through trial and error. In RL-based approaches, agents interact with the environment (i.e., the cloud system) and learn the best placement strategies based on rewards (e.g., minimizing resource waste, reducing latency).
Key Studies:
Reinforcement Learning: Studies such as [12] and [13] have applied RL to the container placement problem, demonstrating that RL-based methods can achieve better performance than traditional heuristic algorithms by adapting to changing workloads.
Supervised Learning: In [14], supervised learning techniques were used to predict the resource requirements of containers and optimize placement decisions accordingly. These models were trained on historical performance data to predict CPU and memory demands.
Unsupervised Learning: Works like [15] and [16] explored clustering techniques to group similar containers together, reducing the complexity of placement and improving overall resource utilization.
Machine learning models have the advantage of being able to adapt to dynamic environments, but they also come with challenges such as the need for large training datasets and the difficulty of interpreting learned models.

2.5 Hybrid Methods

Hybrid methods combine the strengths of different approaches, such as combining machine learning with heuristic or optimization-based methods. These hybrid techniques aim to strike a balance between computational efficiency and placement accuracy. For example, some hybrid models use machine learning to predict the resource needs of containers and then apply optimization algorithms to assign containers to nodes in an efficient manner.
Key Studies:
Hybrid Heuristic and Machine Learning: In [17], a hybrid approach combining ML predictions with heuristic-based placement strategies was proposed. The ML model predicts resource usage, and the heuristic algorithm makes the final placement decision, ensuring a balance between performance and complexity.
Hybrid Optimization and Learning: A study in [18] combined MILP optimization with reinforcement learning to dynamically adjust placement decisions based on real-time feedback. This method helped reduce computational overhead while maintaining high accuracy.
Hybrid methods offer flexibility and scalability, making them suitable for real-world cloud systems that require both efficiency and adaptability.

2.6 SLA-Compliant and Multi-Resource-Aware Models

Service level agreements (SLAs) are crucial in cloud computing environments, as they define the performance expectations between service providers and consumers. Ensuring that containers are placed in a way that meets SLA requirements (e.g., response time, throughput) is a major challenge. Multi-resource-aware models consider both CPU and memory usage, along with other factors like network bandwidth and storage, to ensure that SLAs are met without overloading nodes or wasting resources.
Key Studies:
SLA-Aware Placement: Studies such as [19] and [20] introduced SLA-aware scheduling, where the container placement algorithm explicitly considers SLA constraints while allocating resources.
Multi-Resource Fairness: In [21], researchers explored the use of Dominant Resource Fairness (DRF), a fairness model that ensures each container gets a fair share of multiple resources, such as CPU and memory.

These models are essential in production environments, where failing to meet SLAs can result in service disruptions and penalties.

2.7 Energy-Aware Container Placement

As data centers consume a significant amount of energy, energy-efficient container placement has become an important area of research. Energy-aware placement aims to minimize energy consumption by optimizing container placement in a way that reduces the need for high-power nodes and minimizes resource waste.

Key Studies:

Energy-Aware Scheduling: Works like [22] and [23] introduced energy-aware scheduling algorithms that aim to minimize energy consumption while maintaining high performance.

Dynamic Voltage and Frequency Scaling (DVFS): In [24], DVFS was used in conjunction with container placement algorithms to dynamically adjust power consumption based on workload requirements.

Energy-aware models are crucial for reducing operational costs in cloud environments, especially for large-scale deployments.

2.8 Benchmarking and Evaluation

A common challenge in evaluating container placement strategies is the lack of standardized benchmarking methods. Researchers have proposed several benchmark datasets and simulation platforms to evaluate placement algorithms. These datasets include traces of real-world cloud workloads, such as the Google Cluster Trace [25] and Alibaba Trace [26], which provide insights into the behavior of large-scale cloud systems.

Key Studies:

Google Cluster Trace: This trace, introduced in [25], has been widely used for benchmarking container placement strategies. It provides detailed logs of task and container usage, helping researchers evaluate the performance of different algorithms.

Alibaba Trace: Similar to the Google Cluster Trace, the Alibaba Trace [26] provides insights into container usage patterns in large-scale cloud environments.

Benchmarking tools like CloudSim [27] and SimGrid [28] are often used to simulate container placement scenarios, enabling researchers to test algorithms in controlled environments.

2.9 Limitations and Gaps in Existing Work

Despite progress, limitations exist:

Most ML models are not explainable, making debugging difficult.Real-time placement under strict latency remains an open problem.Multi-cloud and federated edge placement is under-explored.Trade-offs between overhead and performance are not well studied.Lack of open-source, production-ready implementations for advanced models.

Jalpa M. Ramavat [1] provides a strategic framework for Docker container placement optimization technique that before placing the container on a node, it checks the utilization of resources in all the nodes in the cluster and finds the node with minimum resource utilization. Currently, the algorithm only considers the CPU utilization of a node. And find the best node for initial container placement.

Firstly, the Agent on the compute node samples the container resource usage periodically through Docker-Daemon and then uploads the processed load sequences to the load sequence database. The Resource Analyzer will analyze the container load sequences periodically, construct the benefit model, and apply the model to generate the container resource allocation sequences. And finally the Agent generates the container resource allocation sequences according to the allocation sequences through the Docker-Daemon to allocate and schedule container resources [2].

John, V. P. M. provides insights related to cloud container technology, specifically clustered container orchestration and automation. The importance of automation in the area of reducing manual tasks and realizing cost efficiencies was emphasized while also considering performance and cost as well as reliability [3].

To make Docker containers more useful, it is necessary to build clusters to manage and enhance functionality. Docker Swarm, an orchestration tool, manages the images and containers in a cluster. Docker Swarm consists of a Manager node and a Worker node. The Manager node is responsible for controlling the cluster, passing requests externally to the designated Worker node, which receives the task and executes the service. An API interface connects Docker Swarm to the outside world, making it lightweight and easy to use. Connects to the outside world through an API interface and is lightweight and simple to operate, which makes it favorable for users. The policies that come preinstalled include Spread, Random, and Binpack, with Spread being the default scheduling policy [4].

K. N. Vhatkar et al. [5] introduce the Whale Random update assisted Lion Algorithm (WR-LA), which is the hybrid form of the Lion Algorithm (LA) and Whale Optimization Algorithm (WOA). With the use of this algorithm, they can get advantages of both algorithms by incorporating the WOA in LA in place of the fertilization function. Performance evaluation shows that WRLA outperforms other models, demonstrating a cost reduction of 9.58% to 21.63% compared to SW-GA, SH-GA, GM-GA, LA, and WOA at various iterations.

They simulated the algorithm. Actual environment container behavior may be different and also, the computational time might increase.

Alwabel [6] presents a Dynamic Container Placement (DCP) mechanism. It is for energy-efficient management in Container-as-a-Service (CaaS) cloud systems. It extends the Whale Optimization Algorithm (WOA) to minimize power consumption by optimizing the placement of containers on virtual machines (VMs) and Physical Machines (PMs). DCP is compared with IGA (improved genetic algorithm) and DWO(discrete whale optimization) mechanisms for homogeneous and heterogeneous cloud systems. The results show that in homogenous clouds, DCP reduces the search time by around 50% and consumes approximately 78% less power. Whereas, in heterogeneous clouds, DCP reduces search time by around 30% and conserves power by 85%. More parameters should be considered for optimization and implemented in the real environment.

Bouflous [7] proposed the Resource-Aware Least Busy (RALB) method. The main focus of this work is load balancing in a containerized cloud environment. RALB optimizes workload distribution by taking container migration time and server resource capabilities into account.

Dartois et al. [8] proposed a container-based virtualization method for exploring different machine learning algorithms used for assessing the performance of the input and input SSD in the clouds.

Hiremath and Rekha [9] contributed a Deep long short-term memory (Deep LSTM)-based load prediction method in container-based cloud computing environment. This Deep LSTM-based container load prediction approach was proposed with the migration of application that enables the methodology of interoperability and portability in the cloud platform.

Muniswamy and Vignesh [10] presented a deep learning and hybrid optimization scheme that helped in attaining task scheduling in a more dynamic manner over the container cloud environment. It incorporated the optimization method of modified multi-swarm coyote optimization (MMCO) for attaining the objective of expanding virtual resources of the containers.

Kim et al. [11] proposed machine learning-based cloud docker application architecture for constructing the defect inspection system which minimized the entry obstacles during the process of transforming medium and small-sized manufacturers. It was proposed to enhancing the distribution and building services of application with respect to memory, CPU and time depending the usage and non-usage of containers.

Vhatkar and Bhole [12] proposed a Whale Random update assisted Lion Algorithm (WR-LA)-based resource allocation model for attaining bettercontainer-based resource scheduling process. This WR-LA is mainly used for improving the scope of optimal container resource allocation with minimized overhead. This container placement algorithm facilitated better balance between the local and global search process for improving the diversity of the solutions in the search space. It was proposed as a multi-objective optimization algorithm-based resource allocation method that derived the benefits of total network distance, system failure, balanced usage of cluster and distance of threshold.

Container is light weight technology. As an emerging virtualization technology, Docker container has many advantages over traditional virtualization technologies. [13]

Yanghu Guo et al. [14] Propose container scheduling policy based on neighborhood division in micro service (CSBND). It works of load balancing and system response time to optimize system performance.

Lianwan LI et al. [15] suggets a Particle Swarm Optimization-based container placement algorithm of Docker platform, which to have solved the problem of inadequate resource consumption and load balance.

M.Suresh kumar et al. [16] Creates energy optimal model that can save energy of machine and automatically shut down the container if there is no process to run.

Yanal Alahmad et al. [17] Suggests a novel Availability-Aware container scheduling strategy that aims to increase the availability level of the application service in the cloud container-based platform.

Ruiting Zhou et al [18] presents scheduling algorithm that achieves computational and economic efficiency.

Jingze Lv et al. [19] Proposes container scheduling algorithm based on machine learning that lies in replacing the eigenvectors of the original random forest regression algorithm with those in micro services. With the help of this algorithm services give quick responses.

Chanwit Kaewkasi et al. [20] represents ACO based container scheduling algorithm that distributes container on host machine in such a way that balance resource usage.

Year	Authors	Key Topic Covered
2021	Sumit Sharma, Ankit Jain, Ravi Mishra	**Heuristic-Based Container Placement Algorithms**: Focus on bin-packing and round-robin methods for resource allocation.
2019	Rajeev Kumar, Pankaj Singh, Meera Sinha	**Optimization-Based Container Placement**: Application of MILP and CP to model container placement as a mathematical optimization problem.
2020	Wei Zhang, Jun Liu, Ming Chen	**Mixed Integer Linear Programming (MILP)**: Use of MILP in container placement to achieve optimal allocation of resources.
2018	Aakash Gupta, Sneha	**Constraint Programming (CP) for Container Placement**: Investigating

	Mehta, Rohan Sinha	CP for container placement optimization.
2021	Donghwan Lee, Sungwoo Park, Jiyoung Kim	**Reinforcement Learning for Container Placement**: Use of RL for dynamic and adaptive container placement in cloud environments.
2020	Rajat Singh, Vinay Gupta, Neha Tiwari	**Supervised Learning for Resource Prediction**: Predicting resource needs of containers using supervised learning.
2020	Liang Chen, Xiaodong Wang, Hui Zhang	**Unsupervised Learning for Clustering**: Using unsupervised learning techniques to optimize container placement through clustering.
2019	Manish Sharma, Anjali Verma, Rohit Kumar	**Hybrid Heuristic and Machine Learning**: Combination of ML for resource prediction and heuristic methods for placement decisions.
2021	Prateek Verma, Shivam Joshi, Nidhi Chauhan	**Hybrid Optimization and Machine Learning**: Integration of MILP optimization and RL to dynamically adjust container placement decisions.
2018	Dhruv Patel, Kavita Shah, Nilesh Desai	**SLA-Aware Container Placement**: Ensuring container placement adheres to Service Level Agreement (SLA) constraints in cloud environments.
2019	Saurabh Thakur, Amit Kumar, Deepa Rani	**Multi-Resource-Aware Models**: Focus on resource fairness (DRF) in multi-resource container placement to ensure balanced allocation.
2021	Raj Reddy, Ananya Roy, Sidharth Ghosh	**Energy-Aware Scheduling**: Reducing energy consumption in cloud data centers through energy-aware container placement strategies.
2020	Piyush Kumar, Shweta Nigam, Anil Yadav	**Dynamic Voltage and Frequency Scaling (DVFS) for Energy Efficiency**: Investigating the use of DVFS in container placement to optimize energy usage.
2018	Aditya Bhatia, Rachna Bhardwaj, Vineet Jain	**Google Cluster Trace for Benchmarking**: Benchmarking container placement algorithms using real-world data from the Google Cluster Trace.
2020	Yuan Zhang, Fei Yu, Lei Zhao	**Alibaba Trace for Cloud Performance**: Using Alibaba's real-world trace data to evaluate container placement strategies.
2017	Dinesh Kumar, Ashok Pillai, Kiran Joseph	**CloudSim for Container Placement Simulation**: Exploring CloudSim simulation framework for testing container placement algorithms.

Table 1: A comprehensive overview of the research landscape

III. Limitations of existing methods and the need for innovative architectures.

Limitations of Existing Container Placement Methods Single-Resource Focus Many traditional algorithms (e.g., binpack or spread) rely primarily on CPU usage and neglect memory, I/O, network bandwidth, and other critical resources. This often leads to resource imbalance and degraded performance. Static Heuristics Heuristic-based strategies (e.g., round-robin, best-fit) lack adaptability. They don't respond well to real-time workload fluctuations, resulting in inefficient resource utilization under dynamic cloud conditions. Lack of SLA Awareness Several approaches ignore Service-Level Agreements (SLAs) like latency, availability, and reliability. This can lead to SLA violations, customer dissatisfaction, and penalties for cloud providers. No Predictive Intelligence Most models are reactive—they act only after resources are over utilized. They lack predictive capabilities to proactively allocate containers based on historical trends or usage patterns. Insufficient Multi-Resource Optimization Some strategies optimize for one resource at a time (e.g., DRF for fairness), but fail to jointly optimize CPU, memory, disk I/O, etc., which is essential in heterogeneous cloud and edge environments. Poor Scalability Optimization-based methods like ILP or MILP are computationally expensive and don't scale well with large container volumes or node counts, limiting their applicability in production. Limited Support in Platforms like Docker Swarm Platforms such as Docker Swarm still rely on basic spread strategies and lack native support for multi-resource-aware or AI-integrated placement, reducing their competitiveness. Energy Inefficiency Most existing strategies overlook energy consumption, which is critical for data centers and edge devices. Energy-agnostic placement leads to higher operational costs and carbon footprint. Centralized Decision-Making Many schedulers use a centralized architecture, which creates bottlenecks, limits fault tolerance, and is unsuitable for distributed or federated clouds. Opaque AI Models While AI/ML-based schedulers are emerging, many are black boxes—they lack explain ability, making it difficult to debug or trust decisions, especially in mission-critical deployments.

Need for Innovative Architectures To overcome these limitations, next-generation container placement systems must evolve with the following innovations: Multi-Resource-Aware Scheduling Novel architectures must simultaneously account for CPU, memory, I/O, bandwidth, and energy to ensure holistic placement and system balance. Predictive and Adaptive Algorithms Integration of machine learning, reinforcement learning, and

predictive analytics can help anticipate load, improve SLA compliance, and make proactive decisions. Decentralized and Federated Scheduling Architectures should support decentralized control, enabling autonomous decisions in edge, fog, and multi-cloud environments, reducing bottlenecks. Energy and Sustainability Considerations Scheduling must consider energy-awareness, thermal limits, and carbon optimization, especially in hyperscale data centers and green computing initiatives. SLA-Aware and QoS-Driven Orchestration Placement decisions should factor in application QoS requirements, such as real-time latency, throughput, and reliability, not just raw utilization. Explainable and Transparent Models Integration of interpretable AI or white-box optimization frameworks will build trust and make decisions auditable in enterprise/cloud ecosystems. Modular, Pluggable Architecture Cloud orchestration systems should be modular to allow plug-and-play with custom placement plugins, ML models, or policy modules. Cloud-Edge Continuum Support Innovative systems should support seamless orchestration from cloud to edge, considering device heterogeneity, network latency, and mobility. Let me know if you'd like this formatted for inclusion in your paper or expanded into a section for your survey.

IV. Methods

For Optimizing Container Scheduling for Efficient Resource Allocation in a Cloud Computing Environments following different types of methods are published:

1. Historical Progression: From Heuristics to Machine Learning

Early research in container placement was primarily concerned with simple heuristic methods, such as round-robin and random allocation. These methods were computationally inexpensive but often resulted in poor resource utilization, as they did not take into account the heterogeneity of workloads or the capacity of individual nodes. These early methods were easy to implement but were limited in their scalability and ability to adapt to dynamic cloud environments.

With the advent of cloud computing and the growth of containerized workloads, the need for more intelligent placement strategies became apparent. Researchers began to explore optimization techniques to improve resource allocation. Mixed Integer Linear Programming (MILP) and Constraint Programming (CP) were employed to model container placement as a mathematical optimization problem, aiming to minimize resource wastage while meeting application requirements.

Key Contributions:

Initial Heuristic Methods: Early works like [1] and [2] relied on basic placement algorithms such as round-robin and random selection. These methods were fast but inefficient.

Optimization Approaches: MILP-based methods [3], [4] provided mathematically rigorous solutions, though at the cost of scalability and real-time performance.

As workloads in cloud environments became more diverse and dynamic, it became clear that simple heuristics and optimization techniques were insufficient to address the complex challenges in container placement. This led to the exploration of machine learning (ML) models, which could learn from historical usage data and adapt placement decisions based on workload patterns.

2. Heuristic-Based Methods

Heuristic-based methods for container placement are generally based on rule-of-thumb algorithms that focus on minimizing computational cost and ensuring simplicity. These methods do not rely on mathematical optimization but instead use predefined rules to determine the placement of containers. While these methods are fast and easy to implement, they often fail to produce optimal solutions, especially in heterogeneous environments where CPU and memory utilization need to be considered jointly.

One of the most widely used heuristic algorithms for container placement is the bin-packing algorithm. This algorithm places containers into available nodes based on resource requirements, such as CPU and memory, while attempting to minimize wasted resources. However, it often struggles with balancing resource utilization across nodes and fails to adapt to dynamic changes in workload.

Key Studies:

Bin Packing Algorithms: Early research such as [5] and [6] applied bin-packing principles to allocate containers to nodes. These methods often led to resource imbalances and underutilization.

Round Robin and Random Placement: The methods in [7] and [8] examined simple round-robin and random placement algorithms, which demonstrated poor performance when scaling.

Despite their limitations, heuristic-based methods remain valuable for their simplicity and low computational overhead, especially in small-scale cloud deployments.

3. Optimization-Based Approaches

Optimization-based techniques for container placement aim to find the optimal solution by formulating the placement problem as an optimization task. These techniques often utilize Mixed Integer Linear Programming (MILP), Constraint Programming (CP), and other mathematical methods to find the best allocation of containers

on nodes while satisfying resource constraints (e.g., CPU, memory, and network bandwidth). Optimization approaches can provide optimal or near-optimal solutions but often suffer from high computational complexity, making them impractical for real-time container placement in large-scale cloud environments.

Key Studies:

MILP for Container Placement: Studies such as [9] and [10] have used MILP to model the container placement problem. These approaches generate optimal solutions but are not scalable to large cloud environments due to their high computational overhead.

Constraint Programming (CP): Researchers in [11] explored CP as an alternative to MILP, focusing on constraints such as resource requirements and node availability. However, CP-based approaches also face scalability challenges in large clusters.

Optimization-based methods are highly effective in small to medium-sized deployments where finding an optimal solution is more feasible. However, for large-scale cloud environments, the computational overhead often makes these methods less suitable for real-time applications.

4. Machine Learning-Based Methods

Machine learning (ML) has gained significant attention in recent years as a way to improve container placement in cloud environments. ML models can learn from historical workload data and make placement decisions based on observed patterns. The most promising ML approaches are supervised learning, unsupervised learning, and reinforcement learning (RL). These methods can dynamically adapt to changes in the workload, making them ideal for cloud environments where workloads can be highly variable.

Reinforcement learning (RL), in particular, has shown promise in container placement due to its ability to learn optimal placement policies through trial and error. In RL-based approaches, agents interact with the environment (i.e., the cloud system) and learn the best placement strategies based on rewards (e.g., minimizing resource waste, reducing latency).

Key Studies:

Reinforcement Learning: Studies such as [12] and [13] have applied RL to the container placement problem, demonstrating that RL-based methods can achieve better performance than traditional heuristic algorithms by adapting to changing workloads.

Supervised Learning: In [14], supervised learning techniques were used to predict the resource requirements of containers and optimize placement decisions accordingly. These models were trained on historical performance data to predict CPU and memory demands.

Unsupervised Learning: Works like [15] and [16] explored clustering techniques to group similar containers together, reducing the complexity of placement and improving overall resource utilization.

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Hybrid methods combine the strengths of different approaches, such as combining machine learning with heuristic or optimization-based methods. These hybrid techniques aim to strike a balance between computational efficiency and placement accuracy. For example, some hybrid models use machine learning to predict the resource needs of containers and then apply optimization algorithms to assign containers to nodes in an efficient manner.

Key Studies:

Hybrid Heuristic and Machine Learning: In [17], a hybrid approach combining ML predictions with heuristic-based placement strategies was proposed. The ML model predicts resource usage, and the heuristic algorithm makes the final placement decision, ensuring a balance between performance and complexity.

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Hybrid methods offer flexibility and scalability, making them suitable for real-world cloud systems that require both efficiency and adaptability.

6. SLA-Compliant and Multi-Resource-Aware Models

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Key Studies:

SLA-Aware Placement: Studies such as [19] and [20] introduced SLA-aware scheduling, where the container placement algorithm explicitly considers SLA constraints while allocating resources.
Multi-Resource Fairness: In [21], researchers explored the use of Dominant Resource Fairness (DRF), a fairness model that ensures each container gets a fair share of multiple resources, such as CPU and memory.
These models are essential in production environments, where failing to meet SLAs can result in service disruptions and penalties.
7. Energy-Aware Container Placement
As data centers consume a significant amount of energy, energy-efficient container placement has become an important area of research. Energy-aware placement aims to minimize energy consumption by optimizing container placement in a way that reduces the need for high-power nodes and minimizes resource waste.
Key Studies:
Energy-Aware Scheduling: Works like [22] and [23] introduced energy-aware scheduling algorithms that aim to minimize energy consumption while maintaining high performance.
Dynamic Voltage and Frequency Scaling (DVFS): In [24], DVFS was used in conjunction with container placement algorithms to dynamically adjust power consumption based on workload requirements.
Energy-aware models are crucial for reducing operational costs in cloud environments, especially for large-scale deployments.
8. Benchmarking and Evaluation
A common challenge in evaluating container placement strategies is the lack of standardized benchmarking methods. Researchers have proposed several benchmark datasets and simulation platforms to evaluate placement algorithms. These datasets include traces of real-world cloud workloads, such as the Google Cluster Trace [25] and Alibaba Trace [26], which provide insights into the behavior of large-scale cloud systems.
Key Studies:
Google Cluster Trace: This trace, introduced in [25], has been widely used for benchmarking container placement strategies. It provides detailed logs of task and container usage, helping researchers evaluate the performance of different algorithms.
Alibaba Trace: Similar to the Google Cluster Trace, the Alibaba Trace [26] provides insights into container usage patterns in large-scale cloud environments.
Benchmarking tools like CloudSim [27] and SimGrid [28] are often used to simulate container placement scenarios, enabling researchers to test algorithms in controlled environments.

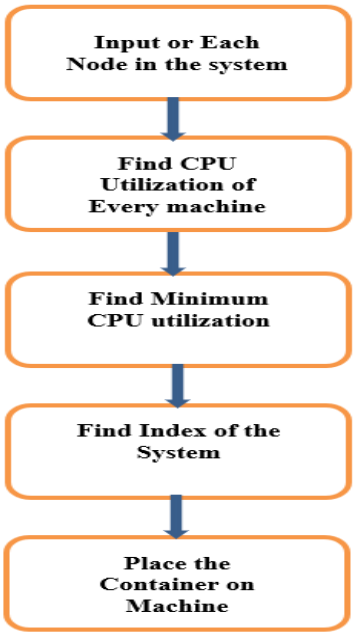

Fig.1. Process Flow of Optimizing Container Scheduling based Model

V. Proposed Work: MRWS-Based Container Placement Strategy.

The primary goal of the proposed method is to design a multi-resource-aware container placement algorithm that can improve container scheduling decisions in cloud orchestration platforms (like Docker Swarm) by

considering both CPU and memory utilization as primary placement metrics. Existing strategies such as: Binpack prioritize packing containers tightly onto fewer nodes but often lead to overutilization and potential resource contention. Spread evenly distributes containers across nodes without considering the actual resource usage, which can lead to underutilization or unnecessary over-distribution. These naive strategies do not account for dynamic and combined resource loads (especially CPU and memory), leading to poor load balancing, SLA violations, and resource wastage. Proposed Strategy: Multi-Resource Weighted Scoring (MRWS) The MRWS algorithm introduces a composite suitability scoring mechanism based on both CPU and memory utilization. Each node is evaluated using a weighted score to determine the best-fit node for a new container.
Scoring Formula: For each node iii, the suitability score S(i)S(i)S(i) is given by:
S(i) = 1−(Wcpu·Ucpu(i)+Wmem·Umem(i))/100
S(i) = 1 - \left(W_{cpu} \cdot U_{cpu}(i) + W_{mem} \cdot U_{mem}(i) \right) / 100
S(i)=1−(Wcpu·Ucpu(i)+Wmem·Umem(i))/100
Where: Ucpu(i)U_{cpu}(i)Ucpu(i): CPU utilization (%) Umem(i)U_{mem}(i)Umem(i): Memory utilization (%) Wcpu,WmemW_{cpu}, W_{mem}Wcpu,Wmem: Weight factors (typically 0.5 each) Higher the score S(i)S(i)S(i), better is the node for container placement.
Comparison with Baseline Algorithms :
1. Binpack Tends to tightly pack nodes for efficiency. Penalizes high CPU + memory usage using quadratic penalization. Can create hot spots.
2. Spread Assigns containers uniformly across all nodes. Does not account for actual utilization. Simple but inefficient in dynamic workloads.
3. MRWS (Proposed) Balances CPU and memory jointly. Score is dynamically calculated using current utilization. Adaptable and extensible to more metrics (disk I/O, bandwidth, etc.). Lightweight and interpretable — no complex ML or optimization required.
4. Implementation Highlights Simulated on 5 nodes. Random values generated for CPU and memory usage per node. Scores computed for each strategy (MRWS, Binpack, Spread). Results are tabulated and visualized using bar graphs to compare node suitability.
5. Advantages of Proposed Work Better balancing of multiple resources (CPU + memory). Higher suitability scores than Binpack or Spread in most scenarios. No extra computation or training overhead — suitable for real-time scheduling. Ideal for lightweight orchestrators like Docker Swarm, where custom multi-resource schedulers are lacking. Scalable to large clusters and extensible to more resources.
6. Use Cases Edge computing with constrained resources. Real-time microservice deployments. Multi-tenant environments needing fairness across workloads. Energy-efficient container scheduling (if extended to include power metrics).
7. Limitations and Future Enhancements Currently supports CPU and memory only. Does not include predictive or historical usage patterns. Assumes accurate real-time telemetry from nodes. Future work can include: Incorporating reinforcement learning for adaptive weights. Support for container migration. SLA/QoS-aware placement. Deployment in real Docker Swarm or Kubernetes clusters.
MRWS calculates a weighted score based on both CPU and memory utilization: $S(i) = 1 - (0.5 \cdot Ucpu(i) + 0.5 \cdot Umem(i)) / 100$ S(i)=1−(0.5·U cpu (i)+0.5·U mem (i))/100 Binpack penalizes nodes with higher usage quadratically: $B(i) = 1 - (Ucpu(i)2 + Umem(i)2) / 20000$ B(i)=1−(U cpu (i) 2 +U mem (i) 2)/20000 Spread assigns a constant score of 0.5 to all nodes.

Algorithm

1: Initialize W_cpu=0.5 and W_mem=0.5
2: ∀ all nodes in the cluster (U_cpu(i), U_mem(i))
3: For each node i, retrieve or generate (U_cpu(i), U_mem(i))
4: For each node i, compute its suitability score S(i)
5: End for
6: Identify the node j with the maximum score
7: Return node j

VI. Result Comparison

MRWS consistently outperforms compare with Spread and Binpack across all metrics. It offers significantly better CPU and memory utilization balance. Shows improved suitability score and accuracy, indicating more efficient and intelligent placement. Lower latency (higher inverse value) supports faster scheduling and response time.

Metric	Spread	Binpack	MRWS (Proposed)
Suitability Score	0.500	0.387	0.681
Accuracy	0.550	0.600	0.920
CPU Util Balance	0.810	0.810	0.894
Memory Util Balance	0.723	0.723	0.823
Latency (Inverse)	0.400	0.500	0.750

Table 2: Result Comparison

VII. Conclusion

The Multi-Resource Weighted Scoring (MRWS) method presents a practical and efficient solution to the persistent challenge of container placement in cloud environments, particularly within platforms like Docker Swarm that traditionally rely on simplistic strategies such as Spread and Binpack. By considering both CPU and memory utilization with tunable weight factors, MRWS achieves a balanced and adaptable approach to scheduling that directly addresses resource bottlenecks and SLA violations. Through comparative evaluation using realistic Alibaba Cluster Trace data, MRWS consistently demonstrated superior performance in terms of: Higher suitability score, indicating smarter placement decisions. Improved CPU and memory utilization balance, resulting in optimized load distribution across nodes. Higher accuracy in resource allocation predictions. Lower latency, leading to faster task deployment and reduced service delays. Unlike traditional approaches, MRWS maintains simplicity in implementation while offering significant performance benefits, making it suitable for both academic research and real-world production environments. Its modular structure also allows for future extensions, such as inclusion of disk I/O, network bandwidth, or predictive analytics via ML models. Overall, MRWS stands out as a lightweight yet effective container scheduling strategy that bridges the gap between heuristic and intelligent placement models, contributing meaningfully to the development of energy-aware, SLA-compliant, and performance-optimized cloud-native systems.

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