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Optimization of Kubernetes for the High-Performance Computing with Kubernetes, Performance Analysis, and Dynamic Workload Placement toward the Enhancement of Cloud Computing

Srinivas Chippagiri

Sr. Member of Technical Staff, *Salesforce Inc*, Seattle, USA
Email: *cvas22 [at] gmail [dot] com*

Abstract: ***The rapid growth of cloud computing has created a demand for efficient resource utilization and high-performance computing (HPC) solutions. An essential component for overseeing cloud workloads is Kubernetes, a top-tier container orchestration platform. However, challenges such as resource underutilization, workload inefficiencies, and performance bottlenecks persist in dynamic cloud environments. This paper presents a comprehensive evaluation of optimizing Kubernetes for high-performance computing (HPC) in hybrid cloud-edge environments. Kubernetes is configured with components such as Etcd, Kube-APIServer, Kube-controller-manager, and Kube-scheduler to enable efficient resource management and workload orchestration. Kubeflow operators are integrated to automate machine learning workflows, including distributed training, hyperparameter tuning, and model serving. Performance metrics were analyzed for two methods, KFT and KFL. KFT achieved a deployment time of 173 seconds, a task completion time of 4.62 hours, CPU utilization of 3.47%, and RAM utilization of 3708 MB. Conversely, KFL demonstrated a faster deployment time of 51.29 seconds, a task completion time of 5.31 hours, CPU utilization of 13.77%, and RAM utilization of 2725 MB. Furthermore, KFT outperformed KFL in accuracy, reaching 0.55 at epoch 10, compared to 0.50 for KFL. These findings highlight a trade-off between resource utilization and performance, offering key insights into optimizing Kubernetes for scalable HPC systems in cloud-native environments.***

Keywords: Kubernetes optimization, high-performance computing, dynamic workload placement, resource efficiency, Kubeflow framework, privacy-preserving computing, cloud computing, computational efficiency

1. Introduction

The fast growth of cloud computing has become a major motivator for large-scale data centers, and it has also become the standard for next-generation information technology [1]. For contemporary data centers, purchasing new servers represents 50%–70% of the total cost of ownership (TCO) [2][3]. However, a number of studies reveal that data center servers often use just 10%–20% of their resources. Growing usage of Bubble-Up in contemporary warehouse-scale computers[4],[5] leads to significant resource waste and expensive operating costs[6].

Additionally, containers are replacing virtual machines as the data center's virtualization solution of choice [7],[8]. Application development and deployment may be significantly streamlined using containers, a lightweight virtualization technique that eliminates virtualization overhead [9][10][11]. As far as container cluster management platforms go, Kubernetes is currently the gold standard [12][13][14]. In addition to its extensive usage in public clouds and business IT systems, Kubernetes is now being utilized by many operators to operate and manage workloads that are neither microservices nor web apps [15]. Typical examples include traditional large data processing, high-performance computing, and ML training [16],[17]. With the release of version 2.3.0, Spark formally added native support for Kubernetes.

Running batch processes concurrently with user-facing, latency-sensitive services might lead to a decrease in the quality of the end-user experience because of competition for shared resources [18]. To address this, Kubernetes typically separates these workloads into different machines, reducing performance interference but resulting in underutilized resources [19][20]. Leveraging Kubernetes for enhancing cloud computing involves optimizing resource allocation to balance workload performance while minimizing inefficiencies [21][22].

The most significant obstacle in Kubernetes's path to improving cloud computing services is selecting higher-performing components to replace native ones and using suitable optimization techniques [23][24]. We want to choose various parts to test and compare them, make concurrent changes to the underlying architecture, and then confirm the findings via extensive trials[25][26]. Thus, prioritize enhancing K8s cloud computing performance by the incorporation of new components and the modification of K8s design [27][28][29].

a) Motivation and contribution of the study

This work aims to optimize Kubernetes for high-performance computing (HPC) in cloud environments, addressing challenges related to resource utilization, dynamic workload placement, and scalability. By enhancing Kubernetes' capabilities, this study aims to improve the efficiency and performance of cloud computing systems, particularly in managing computationally intensive tasks like machine learning and simulations across hybrid cloud and edge setups. The contribution of study is as:

- Proposes strategies for optimizing Kubernetes to handle high-performance computing workloads efficiently in cloud environments.
- Develop an approach for dynamic workload placement based on resource availability and computational demand, ensuring optimal resource utilization.
- Conducts a comprehensive performance analysis of Kubernetes-based systems in cloud environments, evaluating key metrics like deployment time, CPU and RAM utilization, and overall system efficiency.
- Demonstrates how Kubernetes can be deployed across both cloud and edge nodes, improving scalability and performance for hybrid cloud architectures.

b) Structure of paper

This is the structure that the rest of the paper follows. Section II provides a literature review on Kubernetes Optimization for High-Performance Computing with Kubernetes, Performance Analysis, and Dynamic Workload Placement towards the Enhancement of Cloud Computing. Section III contains methods and methodologies, and Section IV involves analysis and discussion of results. Section V presents the study's conclusion and plans for advancement.

2. Literature Review

In this section, previous studies have explored optimizing Kubernetes for high-performance computing by improving resource allocation, workload placement, and system efficiency. Research also highlights advancements in auto-scaling, disaster recovery, and zero-downtime updates, enabling Kubernetes to handle increased workloads while maintaining efficiency in cloud-native environments.

In, Zhang et al. (2021) introduces Zeus, a cluster scheduling solution built on top of Kubernetes extension methods and meant to be extremely scalable. Protected colocation of best-effort tasks and latency-sensitive services is accomplished by Zeus. Zeus may also dynamically distribute resources between the two types of workloads and schedule best-effort processes according to actual server utilization. Further, Zeus improves container isolation by integrating hardware and software isolation capabilities. Consequently, Zeus is able to enhance Kubernetes cluster resource utilization. Findings demonstrate that Zeus may achieve a 15% to 60% increase in average CPU utilization without SLO violations by co-locating latency-sensitive services with best-effort workloads[30].

In, Han, Hong and Kim (2020) provide a framework for improving the placement of microservices based on profiling in order to detect and effectively react to workload factors. We extract delicate resource needs from profiling studies with specified workloads to attain this purpose. We next use a greedy-based heuristic approach to position microservices, taking application performance into account via the utilization of resource needs determined by the profiled findings. Lastly, we compare the experimental findings that include our work with those that do not, in order to confirm the suggested notion[31].

In, Vasireddy, Kandi and Gandu (2023) consequences of load balancing on the efficiency and scalability of applications running on Kubernetes clusters. Thinking about things like reaction speed, throughput, and flexibility to diverse workloads, it investigates the costs and benefits of various solutions. Load balancing in dynamic container orchestration systems is becoming more and more important as cloud-native designs change. Researchers and practitioners may benefit from our synthesis of the existing literature on Kubernetes load balancing, which lays the groundwork for future developments in the pursuit of distributed systems that are efficient, scalable, and robust[32].

In, Sai et al. (2024) fully commits to the field of improving OpenStack and Kubernetes in the context of edge computing, with a particular emphasis on optimizing performance and refining methods for allocating resources. This research aims to discover new ways to improve these platforms' functionality by carefully analyzing the difficulties of resource allocation and exploring the subtleties of performance improvement by investigating how OpenStack and Kubernetes may work together to manage infrastructure and containers more effectively[33].

In, Yadav (2024) delves into the possible uses and advantages of using AI algorithms in Kubernetes settings, spotlighting important domains like auto-scaling, optimized deployment techniques, predictive maintenance, cost optimization, and continuous optimization, among others. Through an analysis of the interplay between Generative AI and Kubernetes, this study brings attention to the potential for better utilization of resources, better application performance, lower infrastructure costs, and higher operational efficiency. It emphasizes the significance of researchers, practitioners, and the open-source community working together to foster innovation and realize the full potential of AI-driven optimizations in Kubernetes[34].

In, Mondal, Zheng and Cheng (2024) aims to optimize zero-downtime rolling updates, reduce data distribution latency, enhance cluster backup and restore strategies for better disaster recovery, incorporate better strategies for load balancing and request handling, optimize autoscaling, introduce better scheduling strategies, and much more. Results demonstrated that the optimized Kubernetes platform could manage 2000 concurrent requests with less CPU overhead (less than 1.5%), less memory (less than 0.6%), shorter average request times (less than 7.6%), and fewer failures (less than 32.4%), all in comparison to the default settings [27].

3. Methodology

The methodology for optimizing Kubernetes for high-performance computing (HPC) in cloud environments involves setting up a hybrid cloud-edge architecture, where cloud nodes (equipped with 4 CPUs, 16GB RAM, and A100 GPU) and edge nodes (with 15 CPUs, 30GB RAM, and P2000 GPU) are interconnected via fiber optics. Kubernetes is deployed to manage resources efficiently across these nodes, with master and worker nodes playing distinct roles in controlling and executing workloads. The system is configured with Kubernetes components like Etcd for cluster coordination, Kube-EPiServer for API interactions, Kube-controller-manager for control loops, and Kube-scheduler for pod management. Additionally, Kubeflow operators are implemented to automate machine learning workflows,

focusing on distributed training, hyperparameter tuning, and model serving, leveraging Kubernetes' scalability and resource management features. Performance analysis is conducted using metrics such as deployment time, complete time, CPU and RAM utilization to evaluate resource efficiency and optimize workload placement dynamically across the cloud and edge nodes for enhanced cloud computing performance.

1) Kubernetes Architecture

Kubernetes is designed using a client-server model. In a multi-master configuration, high availability is achievable; however, in the usual configuration, a single server serves as the controlling node and point of contact [35][36]. Figure 1 shows the Kubernetes architecture. According to Kubernetes's Master-Slave paradigm, there are two types of nodes: Master and Worker[37][38]. The Master node acts as the hub of the Kubernetes cluster, performing all necessary administration and control tasks [39][40]. Key components that operate on the Master node include:

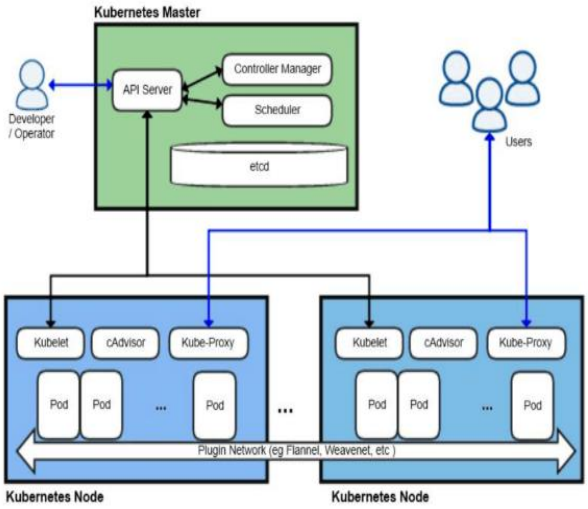

Figure 1: Kubernetes Architecture

- **Etcd:** Data needed to coordinate the cluster's configuration and resources among its many components is stored in a distributed key-value database [41][42].
- **Kube-EPiServer:** Makes available the Restful interface, the only means of accessing the cluster capabilities [43][44].
- **Kube-controller-manager:** The Kubernetes core control loops are embedded by this daemon [45]. Control loops are nonterminating loops that govern the system's status in robotics and automation applications [46][47].
- **Kube-scheduler:** It iteratively chooses Pods waiting in line and places them on nodes that have enough of the needed resources [48]. As the most fundamental object that may be produced, scheduled, and deployed, a pod consists of one or more containers that share storage and network resources as well as a specification for how to operate the containers[49].

2) Kubeflow operator (KFL)

An essential part of Kubeflow, an open-source platform intended to make managing and deploying machine learning workflows on Kubernetes easier, is the Kubeflow Kubernetes operator. Operators in Kubeflow, such as TFJob, PyTorchJob, and Katib, automate the orchestration of ML-specific tasks like distributed training[50], hyperparameter tuning, and model serving[51][52]. These operators leverage Kubernetes' native capabilities for scalability and resource management, enabling seamless integration and optimization of ML workflows in containerized environments[53]. Native automation of stateful apps is not possible with solitary K8s. We have developed K8s operators to handle this issue. By enhancing the Kubernetes API, these third-party controllers simplify the administration and deployment of complicated applications[54]. They enable automated activities like scalability, upgrades, and backups by encapsulating operational information. By encoding application-specific characteristics, operators improve K8s capabilities, making them more dynamic, adaptable, available, and flexible for unique personalized control loops[55].

3) KubeFATE (KFT)

When it comes to production settings, KubeFATE is the way to go for a solitary deployment. It employs a KubeFATE client binary package with YAML settings to personalize the rollout of exchanges and parties [56][57]. The four main components of a party deployment are the following: the roll site pod, which facilitates contact between the parties, the destiny board pod, which keeps tabs on everything, the client pod, which houses a Jupiter notebook, and the python pod, which hosts the fate flow container and a MySQL client [58][59]. Each participant in a Kubernetes (k8s) cluster is contained inside its own namespace when it is deployed. It is possible for many FATE clusters to cohabit on one or more clusters, with SSH allowing access across pods at various roll sites. In this way, pods may be guaranteed to stay on their designated nodes even after several trials[60]. The configuration allocated resources among nodes in the following way: the exchange was hosted by node C1, two parties by node C2, one party each by nodes E1 and E2, and three parties each by nodes E3 and E4. Even though GPUs are compatible with KubeFATE, we refrained from using them in our tests[61][62].

4) Testbed implementation

The situation was replicated via tests conducted at the Smart Internet Lab's Networking Testbed, which comprises of one main node (the cloud) and one set of edge nodes [63][64]. A control plane is located in the main node, and these nodes are linked via fiber. The complexity of FL systems makes it difficult to deploy them across a variety of decentralized clients.

Table 1: System Configuration for Cloud and Edge Nodes

System Configuration	Node	
	C=cloud	*E=Edge*
CPU	4	15
RAM	16	30
Storage	80	100
GPU	A100	P2000

5) Performance Matrix

There is some performance used for Deployment and Resource Utilization Across Methods[65]. The following performance matrix are explained in below:

a) Deployment Time

Deployment time is a metric that measures the amount of time it takes to deploy software to a production environment[66]It is used to measure the efficiency of the deployment process and identify areas for improvement[67]. The formula for Deployment Time is Eq. (1):

$$deployment\ time = End\ Time - Start\ Time$$

It is calculated by measuring the amount of time it takes to deploy software from the moment it is ready to be deployed until it is fully deployed in the production environment. The unit of deployment time is typically in hours, minutes, or seconds.

b) Complete Time

The time required for all the processes or the workflow to complete starting from start to end. Usually, it measures how long it takes a system to finish all tasks in experiments or deployments and is generally indicated in hours or any units of time this is known as complete time[68][69]. This is a metric that gives an idea about how best a method should perform in terms of time efficiency and how well it performed overall[70]. The following Eq. (2):

$$Complete\ Time = End\ Time - Start\ Time$$

c) CPU Utilization

CPU Utilization is the percentage of the central processing unit (CPU) that is used by a system, application or method when executing. But it reveals how well the CPU is being utilized [71]. Low CPU usage suggests more efficient processing while high utilization suggests processor-intensive computational demand. The following Eq. (3):

$$CPU\ Utilization\ (\%) = \left(\frac{Total\ CPU\ Time\ Available}{Total\ CPU\ Time\ Available}\right) \times 100$$

d) RAM Utilization

RAM Utilization is the usage, or amount, of Random-Access Memory (RAM) used during the execution of a process or workflow. It works in megabytes (MB) or gigabytes (GB) and shows how much memory the system or application needs to run. Smooth operation without memory overflow, or lag, is enabled through efficient utilization of RAM[72][73][36]. It is formulated by Eq. (4):

$$RAM\ Utilization\ (\%) = \left(\frac{TRAM\ Used\ (MB/GB)}{Total\ RAM\ Available(MB/GB}\right) \times 100$$

The proposed system's performance is assessed using these metrics.

4. Results and Discussion

The results of comparing the suggested Kube Flower to the benchmarks are shown and discussed in this section. Important parameters, such as deployment time and completion time, CPU utilization, and RAM utilization, are evaluated in this research. Measure time-related metrics, which provide information about the system's efficiency, by keeping track of how long it takes to complete the deployment process. Through this research, we want to learn important things about the system's overall performance characteristics in the cloud-native architecture. Table II presents the KFT and KFL performance based on performance measurement.

Table 2: Performance Metrics Comparison for Deployment and Resource Utilization Across Methods

Methods	Deploy time (s)	Complete time (h)	CPU utilization	RAM utilization
KFT	173	4.62	3.47	3708
KFL	51.29	5.31	13.77	2725

Table II presents a comparative analysis of two methods, KFT and KFL, based on deployment time, completion time, CPU utilization, and RAM utilization. KFT demonstrates a longer deployment time (173 seconds) compared to KFL (51.29 seconds), but it achieves a faster completion time of 4.62 hours compared to 5.31 hours for KFL. In terms of resource utilization, KFT shows lower CPU usage at 3.47% but significantly higher RAM usage at 3708 MB. On the other hand, KFL balances efficiency with higher CPU usage at 13.77% and reduced RAM utilization of 2725 MB. These results highlight a trade-off between resource efficiency and performance, with KFL excelling in deployment speed and memory efficiency, while KFT offers advantages in CPU utilization and task completion speed.

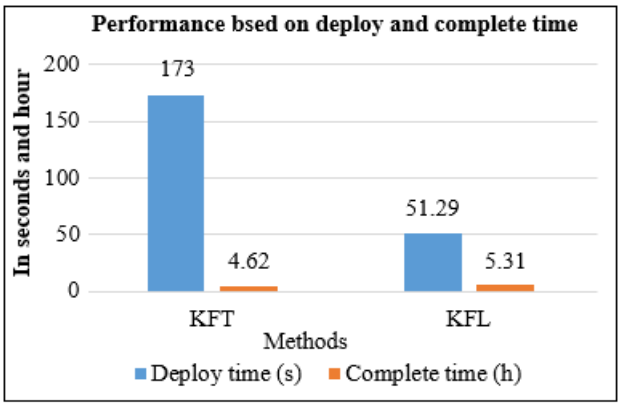

Figure 2: Performance based on deployment and complete time

Figure 2 illustrates the performance comparison of KFT and KFL based on deploy time (in seconds) and complete time (in hours). KFT has a significantly higher deployment time of 173 seconds, while KFL completes deployment much faster at 51.29 seconds. However, when it comes to completion time, KFT performs slightly better, finishing tasks in 4.62 hours, compared to 5.31 hours for KFL. This analysis highlights the trade-off between the two methods, with KFL being more efficient for rapid deployment and KFT excelling in faster task completion.

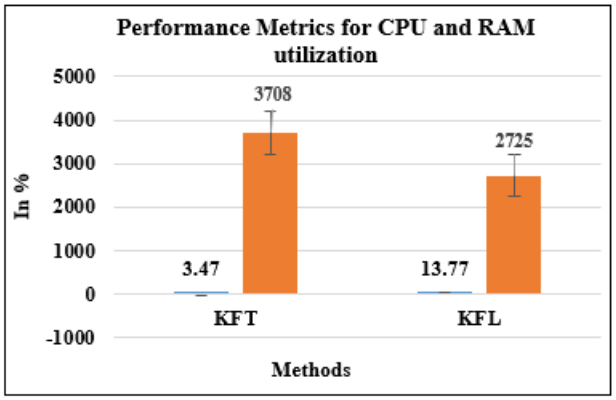

Figure 3: Performance Metrics for CPU and RAM utilization

Figure 3 compares the CPU utilization (%) and RAM utilization (in MB) of the methods KFT and KFL, highlighting a clear trade-off between processing power and memory usage. KFT exhibits significantly lower CPU utilization at 3.47%, making it more efficient in terms of processing

demands. However, this comes at the cost of higher RAM utilization, consuming 3708 MB. In contrast, KFL shows higher CPU usage at 13.77% but is more memory-efficient, utilizing only 2725 MB. This analysis demonstrates that KFT is more suitable for CPU-intensive tasks, while KFL is optimized for memory-constrained environments.

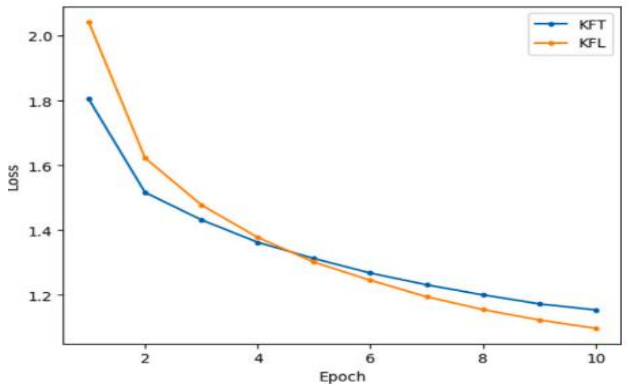

Figure 4: Loss curves for KubeFATE and KubeFlower for 10 epochs.

Figure 4, comparing the **loss** values over **epochs** for two different methods or models, labeled "KFT" and "KFL." The y-axis displays the loss values, which roughly range from 1.0 to 2.0, while the x-axis indicates the number of epochs, which ranges from 1 to 10. Both methods start with high loss values at epoch 1 and show a decreasing trend over subsequent epochs, indicating improved performance. The "KFL" method shows slightly lower loss values compared to "KFT" across all epochs, suggesting better performance in reducing the loss. The graph uses different colored lines with markers for distinction: blue for "KFT" and orange for "KFL."

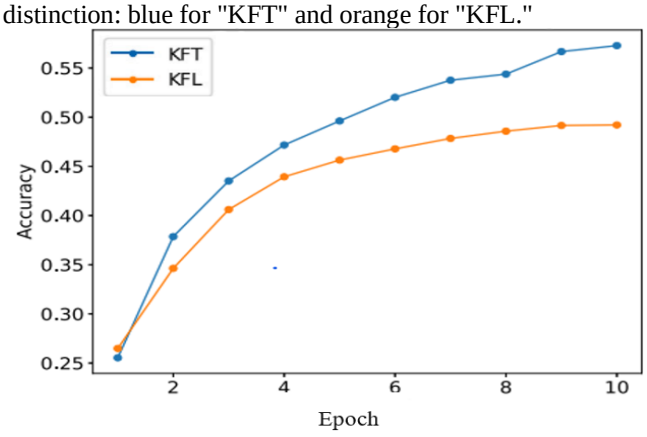

Figure 5: Accuracy curves for KubeFATE and Kubeflow for 10 epochs.

Figure 5 compares the **accuracy** over **epochs** for two methods, "KFT" and "KFL." The x-axis represents the number of epochs (1 to 10), and the y-axis represents accuracy values (ranging from 0.25 to 0.55). Both methods show increasing accuracy as epochs progress. The "KFT" method (blue line) consistently achieves higher accuracy than "KFL" (orange line) across all epochs, demonstrating better performance. The gap between the two methods widens as the epochs increase, with "KFT" surpassing 0.55 accuracy by epoch 10, while "KFL" plateaus below 0.50.

5. Conclusion and Future Scope

The proliferation of microservices has led many businesses to use containerization for their application deployment strategies. If you're looking for a technology to streamline container management, one of the most popular options is Kubernetes. The node's resource request rate is the primary reference statistic for Kubernetes' default scheduler. Container scheduling is given precedence on nodes with low rates of resource requests. To get a node's resource application rate, take its overall resource count and divide it by the quantity of resources it has requested. This study demonstrates the potential of Kubernetes in optimizing HPC in hybrid cloud-edge environments by analyzing the trade-offs between two methods, KFT and KFL. While KFT excels in faster task completion 4.62 hours and higher accuracy (0.55 at epoch 10), it incurs longer deployment time (173 seconds) and higher RAM utilization 3708 MB. In contrast, KFL offers rapid deployment (51.29 seconds) and better memory efficiency 2725 MB but with slightly lower task performance. The study highlights limitations, such as the need for more advanced dynamic workload balancing and energy efficiency in distributed environments. Future research could explore adaptive resource allocation strategies, integration of energy-aware scheduling algorithms, and enhanced support for edge-specific workloads to further optimize Kubernetes for diverse and scalable HPC applications.

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