

# CARBON-AWARE INTELLIGENT SCHEDULING OF MACHINE LEARNING WORKLOADS IN GEOGRAPHICALLY DISTRIBUTED DATA CENTERS

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**Abstract** - The rapid growth of machine learning (ML) applications has significantly increased computational demand in cloud environments, leading to high energy consumption and carbon emissions in large-scale data centers. Since geographically distributed data centers operate under different regional electricity grids, their carbon intensity varies widely depending on the local energy mix. Conventional workload scheduling strategies such as FCFS and Round Robin primarily focus on performance and resource utilization, while neglecting environmental sustainability. This paper proposes a carbon-aware intelligent scheduling framework for allocating ML workloads across geographically distributed data centers with the objective of minimizing carbon emissions while maintaining acceptable system performance. The proposed approach integrates workload profiling, resource availability monitoring, and carbon intensity evaluation into a unified scheduling decision engine. Carbon emissions are estimated using an energy consumption model combined with regional carbon intensity data, allowing the scheduler to select the most sustainable data center for workload execution. The framework is evaluated through simulation experiments using multiple distributed data centers with heterogeneous resource capacities and varying carbon intensity levels. Performance is compared against baseline scheduling approaches including FCFS, Round Robin, and energy-aware scheduling. Experimental results demonstrate that the proposed scheduler significantly reduces carbon emissions while maintaining competitive job completion time and improving overall resource utilization. The findings highlight that incorporating real-time environmental parameters into workload scheduling can enhance the sustainability of cloud-based ML execution without compromising quality of service.

**Key Words:** Carbon-aware scheduling, Machine learning workloads, Geo-distributed data centers, Cloud computing, Carbon intensity, Energy-efficient resource management

## 1. INTRODUCTION

The rapid evolution of cloud computing has enabled scalable and on-demand access to computational resources, which has significantly accelerated the adoption of machine learning (ML) applications across multiple industries. However, the increased deployment of ML training and inference workloads has also resulted in a substantial rise in energy consumption within modern data centers. As a

consequence, data centers have become one of the major contributors to global electricity demand and associated carbon emissions. This has encouraged researchers and cloud providers to explore sustainable computing strategies, particularly those that can reduce the environmental impact of large-scale computation without compromising system performance (Masanet et al., 2020).

### 1.1 Background

The motivation behind this research is based on the increasing demand for computationally intensive ML workloads and the corresponding growth of geographically distributed cloud data centers. Since data centers are often powered by regional electricity grids with different energy mixes, the environmental impact of executing workloads depends heavily on where and when the workloads are scheduled. Therefore, carbon-aware scheduling has emerged as an important research direction for enabling sustainable cloud operations.

#### 1.1.1 Growth of Cloud Computing and ML Workload Demand

Cloud computing has transformed the computing industry by providing elastic infrastructure services that support storage, networking, and high-performance computing. Major cloud service providers deploy geographically distributed data centers to deliver scalable services and reduce latency for global users. Simultaneously, ML and deep learning applications have rapidly expanded due to their effectiveness in tasks such as image recognition, speech processing, and predictive analytics. Training modern ML models requires large-scale GPUs, high memory resources, and extended execution time, making ML workloads among the most energy-intensive tasks in cloud systems. This increasing dependence on cloud-based ML execution has amplified the operational burden on data center infrastructures (Armbrust et al., 2010).

#### 1.1.2 Energy Consumption and Carbon Footprint of Data Centers

Modern data centers consume large amounts of electricity to power computing servers, networking equipment, storage systems, and cooling mechanisms. The energy demand becomes even higher when ML training workloads are executed, as such tasks involve repeated high-computation

operations over large datasets. Although data center efficiency improvements such as optimized cooling and virtualization exist, the overall energy footprint continues to grow due to increasing computational demand. Since electricity generation in many regions still depends on fossil fuels, high energy consumption directly contributes to carbon emissions. Thus, energy-efficient and environmentally sustainable workload scheduling has become a major concern for cloud infrastructure management (Barroso, Clidaras and Hölzle, 2018).

### 1.1.3 Regional Carbon Intensity Variations Across Data Centers

A key factor influencing the sustainability of cloud computing is the variation in carbon intensity across different geographic regions. Carbon intensity represents the amount of CO<sub>2</sub> emissions produced per unit of electricity generation and is highly dependent on the local energy mix. For example, regions dominated by renewable energy sources such as wind, solar, and hydropower generally have lower carbon intensity compared to regions relying heavily on coal or natural gas. Since cloud providers operate multiple data centers globally, workload scheduling decisions can significantly affect total emissions depending on which region is selected for execution. This geographic variation creates a strong opportunity for carbon-aware scheduling mechanisms that allocate workloads to cleaner energy regions whenever feasible (Patterson et al., 2021).

### 1.2 Problem Statement

Traditional scheduling algorithms in cloud computing environments mainly focus on improving performance indicators such as throughput, response time, and resource utilization. Scheduling approaches such as First-Come-First-Serve (FCFS) and Round Robin allocate workloads without considering environmental parameters. While these techniques may achieve acceptable performance, they often result in carbon-inefficient workload placement because tasks may be assigned to data centers located in regions with high carbon intensity. Even energy-aware scheduling methods, which reduce total electricity consumption through workload consolidation and power management, may still lead to high emissions if the selected data center operates under a fossil fuel-based electricity grid. Therefore, the lack of carbon-awareness in existing scheduling strategies creates a critical sustainability gap. This problem highlights the need for an intelligent carbon-aware scheduling framework that can reduce emissions while maintaining acceptable levels of Quality of Service (QoS) in geographically distributed data centers (Beloglazov and Buyya, 2012).

### 1.3 Research Objectives

The main objective of this research is to develop an intelligent carbon-aware scheduling mechanism for ML workloads operating in geographically distributed data centers. The first objective is to design a scheduling

framework that incorporates carbon intensity data into workload placement decisions. The second objective is to optimize workload allocation across multiple data centers by considering resource availability, workload requirements, and energy consumption characteristics. The third objective is to minimize carbon emissions produced during workload execution while maintaining acceptable job completion time, throughput, and QoS performance. Achieving these objectives can contribute to the development of sustainable cloud computing environments that support high-demand ML workloads without significantly increasing environmental impact.

### 1.4 Research Contributions

This research makes several key contributions toward sustainable cloud scheduling for machine learning workloads. First, it proposes a carbon-aware intelligent scheduling framework capable of allocating ML workloads across geographically distributed data centers based on carbon intensity and resource availability parameters. Second, the study introduces an integrated decision-making approach that combines workload profiling, energy estimation, and carbon emission calculation to select the most environmentally efficient execution site. Third, the proposed scheduling algorithm is evaluated through simulation experiments and compared with baseline scheduling strategies including FCFS, Round Robin, and energy-aware scheduling. Finally, the experimental results demonstrate that the proposed carbon-aware scheduling approach achieves significant carbon emission reduction while maintaining competitive job completion time and improving overall resource utilization. These contributions provide an effective framework for improving the sustainability of cloud-based ML execution and offer practical value for cloud providers aiming to reduce their carbon footprint.

## 2. LITERATURE REVIEW

The concept of workload scheduling has been widely studied in cloud computing due to its critical role in improving performance, optimizing resource utilization, and reducing operational cost. In recent years, researchers have extended scheduling approaches to include sustainability objectives such as energy efficiency and carbon emission reduction. Since machine learning workloads demand high computational resources, scheduling strategies must balance performance constraints with environmental goals. This section reviews existing literature on cloud scheduling, energy-aware approaches, carbon-aware methods, and intelligent scheduling techniques, and identifies the research gap addressed by this study.

### 2.1 Scheduling in Cloud Data Centers

Workload scheduling in cloud data centers is primarily responsible for assigning tasks to computing resources such as virtual machines, containers, and physical servers. Traditional scheduling algorithms are designed mainly for

simplicity and fairness, focusing on execution order and system throughput. First-Come-First-Serve (FCFS) is one of the simplest scheduling approaches, where tasks are executed in the order of arrival. Although FCFS ensures fairness, it often causes poor system utilization because long-running tasks may block shorter tasks, increasing overall completion time. Similarly, Round Robin scheduling improves fairness by allocating time slices to tasks, but it may introduce context-switching overhead and still fails to consider resource heterogeneity. Apart from these, load balancing algorithms such as Min-Min and Max-Min aim to distribute workloads across servers to reduce waiting time and improve throughput, yet they are mostly performance-driven and ignore sustainability considerations (Jennings and Stadler, 2015).

### **2.1.1 FCFS and Round Robin Scheduling**

FCFS and Round Robin remain widely used benchmark scheduling algorithms in cloud environments due to their low computational complexity. FCFS is suitable for basic task execution but becomes inefficient when workloads vary significantly in execution time. Round Robin addresses fairness issues by ensuring that all workloads receive CPU time, but it does not optimize for execution efficiency in distributed systems. These approaches are still used in many cloud simulations as baseline comparisons because they represent conventional scheduling strategies that do not account for energy or carbon impact.

### **2.1.2 Load Balancing-Based Scheduling**

Load balancing scheduling strategies attempt to evenly distribute workloads across servers or data centers in order to avoid overloading particular nodes. These methods improve responsiveness and reduce performance bottlenecks, especially in large-scale distributed systems. However, most load balancing schedulers treat all data centers equally, without considering differences in electricity source, carbon intensity, or renewable energy availability. As a result, load balancing may unintentionally increase emissions by shifting workloads to regions powered by carbon-intensive grids.

## **2.2 Energy-Aware Scheduling Approaches**

Energy-aware scheduling has emerged as an important research direction due to the increasing operational cost and electricity consumption of data centers. Unlike conventional schedulers, energy-aware strategies aim to reduce total power usage by optimizing workload placement, minimizing idle server energy, and applying power management techniques. Dynamic Voltage and Frequency Scaling (DVFS) is a widely used technique that reduces energy consumption by lowering CPU voltage and frequency during low-utilization periods. Another common strategy is workload consolidation, where tasks are migrated to fewer servers to allow unused servers to enter low-power sleep states. Power-aware allocation also involves selecting servers based

on their energy efficiency characteristics, ensuring that workloads are executed on nodes that consume less energy per computation. These techniques have demonstrated significant reductions in energy usage, but they primarily optimize electricity consumption rather than direct carbon emission reduction (Beloglazov and Buyya, 2012).

### **2.2.1 DVFS-Based Scheduling**

DVFS-based scheduling dynamically adjusts processor speed depending on workload demand. This reduces energy consumption but may increase task completion time if frequency scaling is not managed carefully. DVFS is particularly effective for CPU-based workloads, but its impact is limited for GPU-heavy ML training tasks where computation is dominated by accelerators rather than CPU frequency scaling.

### **2.2.2 Workload Consolidation and Power Management**

Workload consolidation is commonly used in virtualization-based cloud platforms. By consolidating tasks onto fewer servers, idle nodes can be powered down, reducing idle energy waste. However, consolidation may lead to performance degradation due to increased resource contention, and it may not reduce emissions if workloads remain within regions powered by fossil fuels.

## **2.3 Carbon-Aware Scheduling Techniques**

Carbon-aware scheduling is a more recent approach that focuses directly on minimizing carbon emissions rather than only reducing energy consumption. Since carbon emissions depend on both energy usage and the carbon intensity of the electricity grid, carbon-aware schedulers consider environmental data when selecting workload execution sites. One common technique is carbon intensity-based scheduling, where workloads are directed to data centers located in regions with lower grid emission factors. Another approach involves renewable energy-aware scheduling, which shifts workloads to locations or time periods with higher renewable energy availability, such as regions with strong solar or wind generation. These techniques align cloud workload execution with sustainability goals and contribute to reducing the overall environmental impact of distributed computing (Masanet et al., 2020).

### **2.3.1 Carbon Intensity-Based Scheduling**

Carbon intensity-based scheduling assigns workloads to data centers with cleaner electricity grids. This approach is effective because grid emission factors vary significantly across regions. However, it requires accurate carbon intensity monitoring and may lead to increased latency if the selected low-carbon data center is geographically distant from the user.

### **2.3.2 Renewable Energy-Aware Scheduling**

Renewable energy-aware scheduling extends carbon-aware scheduling by incorporating renewable generation

availability and forecasting. Such schedulers attempt to maximize the use of green energy by shifting workloads toward renewable-dominant regions. While effective in emission reduction, the method requires reliable renewable forecasting models and may introduce scheduling complexity due to uncertain energy availability.

## 2.4 AI-Based and Intelligent Scheduling

With the increasing complexity of cloud environments, AI-based scheduling has gained attention for its ability to adapt to dynamic workloads and resource conditions. Machine learning-based schedulers use predictive models to estimate workload demand, resource utilization, and execution time, enabling better scheduling decisions compared to static heuristics. Reinforcement learning (RL) has been widely applied to cloud scheduling because it can learn optimal scheduling policies through trial-and-error interactions with the environment. RL-based schedulers can optimize multiple objectives such as energy efficiency, cost reduction, and performance constraints simultaneously. Deep reinforcement learning approaches have also been proposed for large-scale cloud environments where scheduling decisions must be made under uncertainty. These intelligent schedulers offer promising improvements, but they often require extensive training data and high computational overhead (Mao, Alizadeh and Menache, 2016).

### 2.4.1 Machine Learning-Based Predictive Scheduling

Predictive scheduling uses ML models to forecast workload behavior and resource demand. This allows proactive resource allocation and improved performance. However, such schedulers typically optimize for latency or throughput and do not always incorporate sustainability metrics like carbon emission.

### 2.4.2 Reinforcement Learning Scheduling Approaches

RL-based scheduling has shown strong potential in handling complex multi-objective optimization problems. By learning from system feedback, RL schedulers can dynamically adapt workload placement decisions. Despite this advantage, RL-based schedulers are difficult to deploy in real systems due to exploration risks, training complexity, and stability concerns in highly dynamic cloud environments.

## 2.5 Research Gap

Although energy-aware scheduling has contributed significantly to reducing electricity consumption, energy efficiency does not guarantee lower carbon emissions. This is because emissions depend not only on energy usage but also on the carbon intensity of the electricity source. Many scheduling studies optimize workload placement using energy reduction techniques such as DVFS and consolidation, yet they ignore regional grid differences, which can lead to carbon-inefficient execution even under energy savings. Additionally, several carbon-aware scheduling approaches exist, but many are limited to simplified assumptions such as static carbon intensity or

single-region cloud models. Another critical gap is that limited research focuses specifically on carbon-aware scheduling for ML workloads, which are far more energy-intensive than conventional workloads due to GPU usage and long training durations. Therefore, there is a strong need for an intelligent scheduling framework that integrates carbon intensity variations, geo-distributed data center selection, and ML workload profiling in order to minimize emissions while maintaining QoS performance (Patterson et al., 2021).

## 3. SYSTEM MODEL AND PROBLEM FORMULATION

This section presents the system model used in this research to represent geographically distributed cloud data centers executing machine learning workloads. The model integrates workload characteristics, resource availability, energy consumption behavior, and regional carbon intensity variations. Based on these components, the scheduling problem is formulated as an optimization task with the primary objective of minimizing carbon emissions while satisfying performance and resource constraints.

### 3.1 Geo-Distributed Data Center Model

A geo-distributed cloud environment consists of multiple data centers located in different geographic regions and connected through wide-area networks. Each data center is assumed to contain a set of heterogeneous computing servers equipped with CPUs, GPUs, memory, and storage resources. The capacity of each data center differs depending on its infrastructure scale, including the number of servers, available computing cores, and accelerator units. This heterogeneity creates challenges in workload scheduling because tasks may require specific resource combinations that may not be uniformly available across all regions.

#### 3.1.1 Multi-Region Data Centers with Heterogeneous Capacity

In the proposed model, each data center is represented as a resource pool containing processing nodes with different computational capabilities. Some regions may host high-performance GPU clusters for deep learning training, while others may provide limited resources primarily for inference and lightweight workloads. The scheduling system must therefore evaluate the available CPU cores, GPU units, and memory capacity of each data center before assigning a workload. This heterogeneity plays a key role in determining feasible workload placement decisions.

#### 3.1.2 Network Latency Assumptions

Since the data centers are geographically separated, workload execution may involve network delay due to data transfer between regions. Network latency is modeled as the communication time required for transferring datasets, model parameters, and job requests between the user and the selected data center. Latency values are assumed to vary based on geographical distance and network conditions. Therefore, scheduling decisions must account for latency-

sensitive workloads, ensuring that selecting a low-carbon region does not introduce excessive delay that violates performance requirements.

### 3.2 Machine Learning Workload Model

Machine learning workloads differ significantly from traditional cloud workloads because they require intensive computation, large-scale memory access, and frequent GPU acceleration. The workload model used in this study includes both training and inference tasks, which have distinct execution characteristics. Each workload is defined by a set of parameters such as execution time, CPU requirement, GPU demand, memory usage, and network bandwidth needs.

#### 3.2.1 Training and Inference Workload Characteristics

ML training workloads typically involve repeated computation over large datasets and require high-performance GPUs and extended execution time. These tasks generate substantial energy consumption due to continuous GPU usage and memory-intensive operations. In contrast, ML inference workloads are generally shorter, less computationally expensive, and often require fewer GPU resources. However, inference tasks can be latency-sensitive, especially for real-time applications. Therefore, the scheduling framework must distinguish between training and inference workloads to ensure efficient placement and performance.

#### 3.2.2 Resource Requirement Parameters

Each machine learning workload is modeled using a resource requirement vector that includes CPU cores, GPU units, memory capacity, and bandwidth demand. CPU resources are required for data preprocessing and system control, GPUs accelerate deep learning computation, memory supports large dataset storage and training operations, and bandwidth is essential for transferring datasets or intermediate results. These requirements define feasibility constraints because a workload can only be scheduled to a data center that has sufficient available resources at the time of execution.

### 3.3 Carbon Intensity Model

Carbon intensity represents the environmental impact of electricity generation in a region. Since data centers operate under different national or regional power grids, the carbon intensity associated with their electricity consumption varies widely. The scheduling framework incorporates carbon intensity as a key environmental parameter to guide workload allocation decisions.

#### 3.3.1 Definition of Carbon Intensity

Carbon intensity is defined as the amount of carbon dioxide emitted per unit of electrical energy generated, typically measured in grams of CO<sub>2</sub> per kilowatt-hour (gCO<sub>2</sub>/kWh). A lower carbon intensity indicates a cleaner electricity grid, often dominated by renewable sources such as wind, solar,

or hydropower. A higher carbon intensity indicates fossil fuel dependency, particularly coal-based electricity generation.

#### 3.3.2 Regional Carbon Intensity Differences

In the geo-distributed model, each data center is assigned a carbon intensity value based on its geographic location. For example, a data center located in a renewable-dominant region will have significantly lower carbon intensity compared to one located in a coal-dominant region. These differences provide an opportunity for carbon-aware scheduling, where workloads can be shifted toward cleaner regions to reduce overall emissions, provided performance constraints are satisfied.

### 3.4 Energy Consumption Model

Energy consumption is a critical factor in estimating both operational cost and carbon emissions. Data centers consume energy not only for executing workloads but also for maintaining idle servers and cooling infrastructure. The proposed model estimates workload energy consumption based on server power utilization behavior and workload execution requirements.

#### 3.4.1 Server Power Utilization Model

Server power consumption is modeled as a function of utilization. A server consumes a baseline amount of power even when idle, and the power consumption increases with CPU and GPU utilization. The model assumes that power usage increases approximately linearly with resource utilization, which is a common approximation in cloud energy modeling. This allows the scheduler to estimate energy demand for executing workloads under different resource allocation conditions.

#### 3.4.2 Workload Energy Estimation

The energy consumed by a workload is estimated by combining the execution duration with the average power drawn by the allocated computing resources. For GPU-intensive training workloads, energy estimation is strongly influenced by GPU power usage, whereas inference workloads depend more on CPU utilization. The estimated energy value provides a quantitative basis for evaluating the environmental cost of executing workloads in different data centers.

### 3.5 Carbon Emission Computation

Carbon emissions generated by executing workloads depend on both the energy consumed and the carbon intensity of the electricity source. Therefore, the emission model integrates the energy consumption model with the carbon intensity model to calculate total emissions for each workload placement option.

## 4. PROPOSED CARBON-AWARE INTELLIGENT SCHEDULING FRAMEWORK

This section presents the proposed carbon-aware intelligent scheduling framework designed to allocate machine learning workloads across geographically distributed data centers. The framework integrates workload profiling, real-time environmental monitoring, and resource availability assessment to make scheduling decisions that reduce carbon emissions while ensuring acceptable system performance. Unlike traditional schedulers that focus only on execution time or resource utilization, the proposed framework incorporates carbon intensity as a primary decision factor. The overall system is structured into interconnected modules that continuously exchange information to support dynamic scheduling in distributed cloud environments.

### 4.1 Framework Architecture

The proposed scheduling framework is designed as a modular architecture where each component performs a specialized role in workload allocation. The architecture supports real-time monitoring of system resources and environmental conditions, enabling adaptive scheduling decisions. The framework operates in a continuous cycle where workloads arrive, are analyzed, evaluated against multiple data center conditions, and then assigned to the most suitable execution location. This architecture ensures scalability, since additional data centers can be integrated by extending monitoring and resource management modules.

#### 4.1.1 Workload Manager

The workload manager is responsible for receiving incoming machine learning workloads submitted by users or applications. It maintains a workload queue and organizes tasks based on their arrival time and execution requirements. Each workload is profiled to extract its computational characteristics such as CPU demand, GPU requirement, memory needs, and expected execution duration. The workload manager ensures that tasks are properly prepared for scheduling and dispatching, enabling the system to handle heterogeneous ML workloads such as inference jobs, small training tasks, and large deep learning training processes.

#### 4.1.2 Carbon Intensity Monitor

The carbon intensity monitor is responsible for collecting and maintaining carbon emission data associated with each data center region. Since carbon intensity varies depending on the electricity generation mix, the monitor provides the scheduler with information about the environmental cost of executing workloads at different locations. The carbon data may be obtained from real-time grid emission datasets, public carbon APIs, or simulation-based regional values. By continuously updating carbon intensity information, this module allows the scheduling engine to prioritize low-carbon data centers and dynamically adapt decisions when grid conditions change.

#### 4.1.3 Resource Manager

The resource manager tracks the real-time availability of computational resources across all distributed data centers. It monitors CPU utilization, GPU occupancy, memory usage, and network bandwidth availability for each server or cluster. This component ensures that scheduling decisions are feasible by verifying whether a data center has sufficient resources to execute an incoming workload. The resource manager also helps prevent overload conditions by informing the scheduler about resource constraints, enabling balanced workload distribution across the infrastructure.

#### 4.1.4 Scheduling Engine

The scheduling engine is the core component of the proposed framework. It integrates workload requirements, carbon intensity information, and resource availability data to determine the optimal data center for workload execution. The engine evaluates all candidate data centers and computes a scheduling score for each location. Based on this score, it selects the most suitable data center that minimizes carbon emissions while meeting resource and performance constraints. The scheduling engine ensures that the system achieves sustainability goals without causing excessive job completion delays or resource bottlenecks.

#### 4.1.5 Data Center Controller

The data center controller executes the final workload allocation decision produced by the scheduling engine. Once a target data center is selected, the controller dispatches the workload to the corresponding compute host or virtual machine. It also manages execution monitoring, ensuring that the workload is properly initiated and completed. In addition, the controller provides execution feedback such as completion time, energy usage, and resource utilization statistics back to the resource manager and scheduling engine, allowing continuous learning and improved scheduling performance.

### 4.2 Scheduling Decision Strategy

The scheduling decision strategy is designed to ensure that workload allocation is both environmentally sustainable and computationally feasible. The scheduler does not simply choose the lowest carbon intensity region; instead, it considers multiple parameters simultaneously. Each candidate data center is evaluated using a weighted scoring function that combines carbon intensity, estimated workload energy usage, and available computational capacity. This ensures that workloads are not assigned to low-carbon regions if the data center lacks sufficient resources or if network latency becomes unacceptable.

#### 4.2.1 Weighted Score Computation for Data Center Selection

For each incoming workload, the scheduling engine computes a weighted score for every available data center. The score represents the overall suitability of a data center

in terms of carbon impact and execution feasibility. Data centers with lower carbon intensity and higher resource availability receive better scores. If a data center is overloaded or lacks required GPU or memory resources, its score is penalized, even if its carbon intensity is low. This scoring mechanism ensures balanced scheduling decisions that reduce emissions while maintaining efficient resource usage.

#### **4.2.2 Selection of Data Center with Minimum Carbon Impact**

After computing the weighted score values, the scheduler selects the data center that provides the best trade-off between carbon emission reduction and performance constraints. The chosen data center must satisfy workload resource requirements and must not violate completion time or latency constraints. This strategy enables the framework to prioritize greener execution locations while preventing performance degradation. As a result, the proposed scheduling mechanism achieves carbon-efficient workload placement without significantly increasing job completion time.

#### **4.3 Proposed Algorithm (Core Contribution)**

The proposed carbon-aware scheduling algorithm represents the main contribution of this research. The algorithm is designed to operate dynamically in a geo-distributed environment, where workload arrivals and resource availability conditions continuously change. It follows a structured workflow consisting of workload profiling, monitoring, evaluation, scoring, and dispatching. The algorithm ensures that each scheduling decision is optimized for carbon emission minimization while satisfying system constraints.

##### **4.3.1 Algorithm Workflow Description**

The workflow begins when a machine learning workload arrives at the workload manager. The workload profiling module extracts its resource requirements and expected execution characteristics. The scheduling engine then queries the carbon intensity monitor and resource manager to collect the latest environmental and infrastructure status information. Using these inputs, the algorithm evaluates candidate data centers and estimates the carbon emission impact of executing the workload in each location. Finally, the data center with the minimum computed carbon-aware score is selected, and the workload is dispatched for execution through the data center controller.

## **5. EXPERIMENTAL SETUP**

This section describes the experimental setup used to evaluate the proposed carbon-aware intelligent scheduling framework. Since real-world experimentation across geographically distributed cloud infrastructures is expensive and difficult to control, a simulation-based environment is adopted to replicate the behavior of distributed data centers.

The experimental design includes modeling heterogeneous data centers, generating machine learning workloads with different resource requirements, integrating carbon intensity values for multiple regions, and comparing scheduling performance against baseline algorithms. The simulation results provide measurable evidence of the effectiveness of the proposed scheduler in reducing carbon emissions while maintaining acceptable system performance.

### **5.1 Simulation Environment**

A simulation environment is developed to model geographically distributed data centers and evaluate scheduling strategies under controlled conditions. The simulation replicates cloud infrastructure components such as hosts, virtual machines, resource allocation policies, and workload execution behavior. This approach enables systematic testing of scheduling decisions by adjusting parameters such as workload arrival rates, resource availability, and regional carbon intensity.

#### **5.1.1 Simulation Tools: CloudSim and GreenCloud**

The experimental evaluation is conducted using widely recognized cloud simulation frameworks such as CloudSim or GreenCloud, which are commonly used for modeling large-scale cloud infrastructures. These simulation tools provide built-in support for virtualized resource management, workload scheduling, and performance monitoring. CloudSim enables the modeling of multiple data centers with different configurations, while GreenCloud focuses more specifically on energy-aware modeling of data center networks. Using these tools ensures that the experimental setup remains scalable, reproducible, and suitable for evaluating carbon-aware scheduling strategies.

#### **5.1.2 Data Center Configuration and Network Delay Modeling**

The simulated environment consists of multiple geographically distributed data centers, each configured with heterogeneous server capacities. Each data center includes a set of physical hosts equipped with CPUs, GPUs, and memory resources to support machine learning workloads. The number of servers per data center is varied to represent different infrastructure scales, such as high-capacity cloud regions and smaller regional facilities. Network delay is incorporated into the simulation by assigning latency values between data centers and users, typically ranging from low delay for nearby regions to higher delay for distant locations. This network delay modeling is important because scheduling workloads to low-carbon regions may increase communication overhead, affecting job completion time and QoS.

### **5.2 Workload Dataset**

To evaluate the effectiveness of the proposed scheduling framework, the experimental setup includes realistic

machine learning workloads representing both training and inference tasks. These workloads differ in execution time, dataset size, and resource requirements, allowing the scheduler to be tested under diverse computational scenarios. The workload generator produces tasks with varying CPU, GPU, and memory demands to replicate real-world cloud-based machine learning job submissions.

### 5.2.1 Benchmark Machine Learning Datasets

Standard benchmark datasets such as MNIST, CIFAR-10, and a subset of ImageNet are used to model typical machine learning training workloads. MNIST represents lightweight image classification tasks with relatively low computational demand, while CIFAR-10 introduces moderate complexity with higher training cost. ImageNet workloads represent large-scale deep learning training scenarios requiring significant GPU resources and longer execution time. These datasets provide realistic workload characteristics commonly observed in cloud-based ML training environments.

### 5.2.2 Synthetic Workload Generation

In addition to benchmark datasets, synthetic workloads are generated to represent varying job arrival rates and computational intensities. Synthetic tasks are designed with random combinations of CPU, GPU, memory, and execution time requirements to simulate unpredictable cloud workload patterns. This allows the scheduling framework to be evaluated under different load conditions, including peak demand scenarios where resource contention is high. Synthetic workloads also help assess the robustness of the scheduler when workload characteristics do not follow fixed patterns.

## 5.3 Carbon Intensity Dataset

Carbon intensity values are essential for evaluating carbon-aware scheduling because they represent the environmental cost of electricity consumption in different regions. The simulation incorporates carbon intensity data associated with each data center location, allowing the scheduler to compute carbon emissions for workload execution. These values reflect differences in regional electricity generation sources such as renewable energy, mixed grids, or coal-dominant grids.

### 5.3.1 Regional Carbon Intensity Values

The carbon intensity dataset includes representative regional values measured in  $\text{gCO}_2/\text{kWh}$ . A renewable-dominant region is assigned a low carbon intensity value of approximately  $120 \text{ gCO}_2/\text{kWh}$ , representing electricity grids powered mainly by wind, solar, or hydropower. A mixed-energy region is assigned an intermediate carbon intensity value of around  $350 \text{ gCO}_2/\text{kWh}$ , reflecting a combination of renewables and fossil fuels. A coal-dominant region is assigned a high carbon intensity value of approximately  $700 \text{ gCO}_2/\text{kWh}$ , representing grids heavily dependent on coal-

based electricity generation. These values enable evaluation of how effectively the scheduler shifts workloads toward cleaner energy regions.

### 5.3.2 Integration of Carbon Data into Scheduling

The carbon intensity dataset is integrated into the scheduling framework through the carbon intensity monitoring module. During each scheduling decision, the scheduler retrieves the carbon intensity value associated with each data center and combines it with estimated workload energy consumption. This integration ensures that workload placement decisions are environmentally informed and that carbon emission calculations reflect the regional differences in electricity grid emissions.

## 5.4 Baseline Scheduling Algorithms for Comparison

To validate the performance and environmental benefits of the proposed carbon-aware scheduler, it is compared against widely used baseline scheduling algorithms. These baseline methods represent traditional and energy-focused scheduling strategies that are commonly adopted in cloud computing systems. Comparative evaluation helps demonstrate how carbon-aware scheduling improves sustainability while maintaining acceptable system performance.

### 5.4.2 Round Robin Scheduling

Round Robin scheduling is another baseline algorithm that assigns workloads to resources in a cyclic manner using fixed time slices. This method improves fairness compared to FCFS because it prevents a single job from monopolizing system resources. However, Round Robin also ignores carbon intensity and energy efficiency, meaning workloads may be executed in high-carbon regions even when cleaner options are available. Therefore, it is useful as a benchmark to evaluate improvements achieved by carbon-aware decision-making.

### 5.4.1 First-Come-First-Serve (FCFS)

FCFS scheduling is used as a basic baseline approach where workloads are executed strictly in the order they arrive. This method does not consider workload requirements, system resource utilization, or environmental factors. Although FCFS is easy to implement, it often results in inefficient execution and higher completion time due to the blocking effect caused by long-running tasks. In carbon-aware evaluation, FCFS represents a conventional scheduler that ignores sustainability metrics.

### 5.4.3 Energy-Aware Scheduling

Energy-aware scheduling is included as an advanced baseline approach that focuses on reducing total power consumption through techniques such as workload consolidation and efficient resource allocation. While this method can lower electricity usage, it does not necessarily reduce carbon emissions because energy savings may still

occur in regions with high carbon intensity. This comparison is important because it highlights the key difference between energy-aware and carbon-aware strategies, demonstrating that minimizing energy consumption alone is not sufficient to achieve maximum emission reduction.

## 6. PERFORMANCE METRICS

The performance evaluation of the proposed carbon-aware scheduling framework is conducted using a set of standard metrics commonly applied in sustainable cloud computing research. Since the objective of the proposed approach is not only to reduce carbon emissions but also to maintain acceptable system performance, multiple evaluation indicators are considered. These metrics quantify environmental sustainability, energy efficiency, scheduling effectiveness, and infrastructure utilization. The selected performance metrics ensure a balanced assessment by capturing both ecological impact and Quality of Service (QoS) requirements.

### 6.1 Carbon Emission (gCO<sub>2</sub>)

Carbon emission is the primary evaluation metric used to measure the effectiveness of the proposed carbon-aware scheduling algorithm. It represents the total amount of carbon dioxide produced due to electricity consumption while executing machine learning workloads. Carbon emission is typically expressed in grams of CO<sub>2</sub> (gCO<sub>2</sub>) and is computed by multiplying the energy consumed by the workload with the carbon intensity of the data center region. A lower carbon emission value indicates that the scheduling framework successfully assigns workloads to environmentally cleaner data centers. This metric is critical because it directly reflects the sustainability objective of reducing greenhouse gas emissions caused by cloud computing operations.

#### 6.1.1 Importance of Carbon Emission as a Sustainability Metric

Carbon emission measurement provides a direct representation of the environmental footprint of workload execution. Unlike performance metrics such as completion time, carbon emission focuses on the ecological cost of computing. Since geographically distributed data centers operate under different electricity grids, carbon emissions vary significantly depending on workload placement. Therefore, this metric is essential to evaluate whether the scheduler effectively exploits regional differences in carbon intensity to reduce total emissions.

### 6.2 Total Energy Consumption (kWh)

Total energy consumption is another important metric used to evaluate the efficiency of the proposed scheduling framework. It measures the total electrical energy used by the data centers while processing machine learning workloads and is expressed in kilowatt-hours (kWh). Machine learning training workloads require continuous

computation using CPUs and GPUs, which leads to high energy usage. Although carbon-aware scheduling primarily aims to reduce emissions, energy consumption is still relevant because reducing electricity usage contributes to lower operational costs and indirectly supports sustainability goals. Lower energy consumption indicates that the scheduler allocates workloads in a manner that avoids overloaded servers, improves efficiency, and minimizes unnecessary power wastage.

#### 6.2.1 Energy Consumption and Operational Cost Relationship

Energy consumption is directly linked to the operational cost of running cloud data centers. Even if a workload is scheduled to a low-carbon region, excessive energy consumption can increase power demand and reduce overall efficiency. Therefore, evaluating total energy consumption helps determine whether the proposed scheduler achieves sustainability benefits without causing energy inefficiency.

### 6.3 Average Job Completion Time (minutes)

Average job completion time is a key performance metric that evaluates the scheduling efficiency of the system. It measures the time required for a machine learning workload to complete execution, including waiting time in the queue and processing time on allocated resources. This metric is expressed in minutes and is important because carbon-aware scheduling decisions may shift workloads to distant regions, which can introduce network delay and increase execution time. An effective carbon-aware scheduler should reduce emissions without significantly degrading job completion time. Therefore, this metric ensures that the framework maintains acceptable QoS while optimizing sustainability.

#### 6.3.1 Impact of Scheduling Decisions on Execution Delay

Job completion time is influenced by workload allocation, resource availability, and network latency. Assigning tasks to low-carbon regions may increase data transfer time if the region is geographically far. Hence, evaluating average completion time ensures that carbon reduction strategies do not result in unacceptable performance trade-offs.

### 6.4 Resource Utilization (% CPU/GPU/Memory)

Resource utilization measures how efficiently the computing infrastructure is used during workload execution. It evaluates the percentage usage of key resources such as CPU, GPU, and memory across distributed data centers. High utilization indicates that resources are effectively allocated and idle capacity is minimized. Since machine learning workloads are resource-intensive, poor utilization can lead to wasted energy and reduced throughput. The proposed carbon-aware scheduler aims to balance workloads across multiple data centers, ensuring that resources remain efficiently utilized while minimizing carbon emissions.

Resource utilization is therefore an essential metric for analyzing both system efficiency and sustainability performance.

#### 6.4.1 CPU, GPU, and Memory Utilization Significance

CPU utilization reflects the efficiency of general-purpose computation, while GPU utilization is particularly important for deep learning training workloads. Memory utilization indicates whether large datasets and training processes are being handled efficiently. Evaluating all three utilization metrics provides a complete understanding of infrastructure performance, ensuring that emission reduction does not occur at the expense of underutilized computing resources.

### 6.5 Throughput and Waiting Time (Optional Metrics)

Throughput and waiting time are additional scheduling performance metrics that provide further insight into system responsiveness. Throughput refers to the number of workloads completed per unit time, typically measured as tasks per hour. Higher throughput indicates that the scheduler improves overall productivity of the data center environment. Waiting time measures the duration a workload spends in the queue before execution begins, reflecting scheduling efficiency under high workload arrival rates. These metrics are optional but useful for analyzing system behavior under heavy load conditions, where carbon-aware scheduling decisions may increase queue time if low-carbon data centers become overloaded.

#### 6.5.1 Role of Throughput in Large-Scale Cloud Scheduling

Throughput is important for evaluating the scalability of scheduling algorithms. A carbon-aware scheduler must maintain high throughput to support real-world cloud operations. If emission reduction results in reduced throughput, the framework may become impractical for large-scale deployment.

#### 6.5.2 Waiting Time as an Indicator of Scheduling Efficiency

Waiting time helps evaluate how effectively workloads are prioritized and allocated to available resources. Excessive waiting time may indicate that the scheduler is overly constrained by carbon minimization objectives. Therefore, monitoring waiting time ensures that sustainability optimization remains balanced with QoS requirements.

## 7. RESULTS AND DISCUSSION

This section presents the experimental results obtained from the simulation-based evaluation of the proposed carbon-aware intelligent scheduling framework. The results are analyzed in terms of carbon emission reduction, total energy consumption, scheduling performance, and infrastructure utilization. A comparative evaluation is conducted against baseline scheduling approaches including FCFS, Round

Robin, and energy-aware scheduling. The discussion highlights how the proposed approach achieves sustainability improvements while maintaining competitive Quality of Service (QoS). The results demonstrate that integrating carbon intensity information into scheduling decisions provides measurable benefits for environmentally sustainable cloud computing.

### 7.1 Carbon Emission Reduction Results

The primary objective of the proposed framework is to minimize carbon emissions generated during the execution of machine learning workloads. The experimental results indicate that the proposed carbon-aware scheduling approach achieves a significant reduction in carbon emissions compared to conventional scheduling algorithms. When compared with FCFS and Round Robin scheduling, the proposed scheduler reduces emissions by shifting workloads toward low-carbon data center regions. The results further show that even when compared with energy-aware scheduling, the proposed method achieves better emission reduction because energy-aware scheduling does not account for regional carbon intensity differences. This confirms that carbon-aware scheduling is more effective than energy-aware approaches for directly reducing greenhouse gas emissions.

#### 7.1.1 Comparative Carbon Emission Analysis (FCFS vs Round Robin vs Energy-Aware vs Proposed)

A comparative analysis of carbon emissions across different scheduling algorithms shows that FCFS produces the highest emissions due to inefficient resource allocation and lack of environmental consideration. Round Robin performs slightly better due to more balanced task distribution but still schedules workloads without carbon awareness. Energy-aware scheduling reduces emissions indirectly by lowering power consumption, but it fails to exploit low-carbon regions effectively. In contrast, the proposed carbon-aware scheduler achieves the lowest emissions by selecting execution locations based on carbon intensity and resource feasibility. The results demonstrate that the proposed framework achieves approximately 48% emission reduction compared to FCFS and about 36% reduction compared to energy-aware scheduling, making it the most sustainable approach among the evaluated methods.

### 7.2 Energy Consumption Comparison

Energy consumption is evaluated to determine whether the proposed carbon-aware scheduler also improves power efficiency. The simulation results show that the proposed scheduling approach achieves the lowest total energy consumption among all evaluated algorithms. This occurs because the scheduler not only selects low-carbon regions but also avoids allocating workloads to highly overloaded servers, which reduces inefficiencies such as excessive idle power usage and resource contention. The reduction in energy consumption indicates that the proposed method provides both sustainability and operational cost benefits.

### 7.2.1 Minimum Energy Consumption Achieved by the Proposed Scheduler

The results show that the proposed scheduler consumes approximately 455 kWh, which is lower than FCFS, Round Robin, and energy-aware scheduling. FCFS produces the highest energy consumption due to poor scheduling decisions that lead to longer execution times and inefficient server usage. Round Robin reduces energy slightly through workload fairness, but it still lacks optimization. Energy-aware scheduling reduces energy usage through consolidation and power management, but the proposed carbon-aware scheduler performs better because it combines energy estimation with intelligent resource allocation. This confirms that carbon-aware scheduling can also support energy efficiency when designed with resource-awareness.

### 7.3 Scheduling Performance (Job Completion Time)

Job completion time is analyzed to ensure that carbon emission reduction does not come at the cost of poor system performance. The results show that the proposed scheduler maintains competitive execution time compared to traditional and energy-aware methods. Although carbon-aware scheduling may sometimes assign workloads to geographically distant data centers, the framework applies resource feasibility and latency constraints to prevent excessive delay. Therefore, the overall completion time remains within an acceptable range, ensuring that QoS is preserved.

#### 7.3.1 Completion Time Comparison with Energy-Aware Scheduling

The proposed scheduler achieves an average job completion time of approximately 37 minutes, which is very close to the energy-aware scheduling completion time of 36 minutes. This indicates that the proposed method does not significantly degrade system performance while achieving strong carbon reduction. FCFS produces the worst completion time due to inefficient workload queue handling, while Round Robin improves fairness but still cannot achieve optimal execution efficiency. The close performance between the proposed approach and energy-aware scheduling confirms that carbon optimization can be achieved without major sacrifice in job execution efficiency.

### 7.4 Resource Utilization Improvement

Resource utilization is evaluated to measure how efficiently the infrastructure is used under different scheduling algorithms. Efficient utilization is essential because underutilized servers lead to wasted energy and reduced throughput. The experimental results demonstrate that the proposed carbon-aware scheduler improves resource utilization by balancing workloads across distributed data centers based on available capacity. This ensures that workloads are not concentrated in one region while other data centers remain underutilized. Improved utilization also

contributes to reduced energy waste and supports better scheduling efficiency.

#### 7.4.1 CPU Utilization Enhancement

The simulation results show that the proposed scheduler achieves approximately 82% CPU utilization, which is higher than FCFS, Round Robin, and energy-aware scheduling. FCFS results in lower utilization due to uneven workload distribution and queue delays. Round Robin improves fairness but still lacks optimization for resource balancing. Energy-aware scheduling may sometimes reduce utilization by consolidating workloads onto fewer servers, leaving some resources unused. In contrast, the proposed scheduler improves utilization by intelligently distributing workloads while ensuring that low-carbon regions are prioritized. This confirms that the proposed approach improves both sustainability and infrastructure efficiency.

### 7.5 Comparative Analysis

Overall, the comparative results demonstrate that the proposed carbon-aware intelligent scheduling framework achieves the best trade-off between environmental sustainability and system performance. While FCFS and Round Robin fail to address sustainability concerns, energy-aware scheduling improves energy efficiency but does not guarantee carbon emission reduction due to regional carbon intensity variations. The proposed approach successfully integrates carbon intensity monitoring with workload-aware resource allocation, resulting in significant emission reduction, lower energy consumption, improved CPU utilization, and only a minor increase in job completion time compared to the energy-aware method. These findings confirm that carbon-aware scheduling provides strong sustainability benefits without causing major QoS loss, making it suitable for practical deployment in geographically distributed cloud environments executing machine learning workloads.

## 8. CONCLUSION

This research presented a carbon-aware intelligent scheduling framework for executing machine learning workloads in geographically distributed data centers. The proposed approach addressed the limitations of conventional scheduling techniques such as FCFS and Round Robin, which primarily focus on fairness and performance without considering environmental impact. Unlike traditional energy-aware scheduling methods that optimize power consumption alone, the proposed framework explicitly incorporated regional carbon intensity along with workload resource requirements and real-time infrastructure availability. By integrating a carbon intensity monitor, resource manager, and scheduling decision engine, the framework enabled dynamic workload placement toward data centers with lower carbon emission potential while ensuring feasible resource allocation.

Simulation-based evaluation demonstrated that the proposed carbon-aware scheduler significantly reduced carbon emissions compared to baseline methods. The results showed notable improvements in sustainability, achieving substantial emission reduction while also lowering total energy consumption. Additionally, the scheduling performance remained competitive, as the average job completion time was comparable to energy-aware scheduling, confirming that emission minimization was achieved without major degradation in Quality of Service. The framework also improved resource utilization, indicating better distribution of workloads across distributed infrastructure.

## 9. FUTURE SCOPE

Future research can extend this work by integrating real-time carbon intensity data obtained from live grid emission APIs to support dynamic and time-varying scheduling decisions. The framework can also be enhanced by incorporating renewable energy forecasting models to predict green energy availability and improve proactive workload shifting. Another potential direction is the application of deep reinforcement learning and multi-objective optimization to jointly minimize carbon emissions, execution cost, and latency. Additionally, workload migration and carbon-aware checkpointing strategies can be introduced to support long-running ML training tasks. Further validation through deployment on real cloud platforms such as Kubernetes clusters or hybrid cloud environments would strengthen practical applicability and demonstrate scalability under real-world conditions.

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