Carbon-Aware Intelligent Scheduling Framework for Energy-Efficient Green Cloud Computing

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ABSTRACT

Cloud computing is widely used in modern industries for storing data, running applications, and managing online services. The rapid growth of cloud computing has significantly increased the energy consumption of large data centers, which also leads to higher carbon emissions and environmental pollution. Most traditional cloud scheduling methods mainly focus on improving system performance and resource utilization without considering energy efficiency and environmental impact. As a result, green cloud computing has become an important research area for developing sustainable and energy-efficient cloud infrastructures. This paper examines various existing studies related to energy-efficient and carbon-aware cloud computing systems. The paper analyzes various approaches to reducing energy consumption and carbon emissions in cloud data centers, including workload prediction, intelligent scheduling, virtualization, carbon-aware resource allocation, and hybrid optimization techniques. Several machine learning and artificial intelligence methods, such as Long Short-Term Memory (LSTM), Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimization (GWO) used in existing research are also discussed. The review mainly focuses on cloud workload management, carbon intensity analysis, and intelligent scheduling strategies used in green cloud computing environments. The analysis of existing studies shows that intelligent scheduling and carbon-aware resource management can significantly reduce energy consumption and environmental impact while maintaining cloud performance and service quality. This review highlights the advantages, limitations, and challenges of current approaches and emphasizes the importance of developing sustainable cloud computing systems for future digital infrastructure.

Keywords: Green Cloud Computing, Energy-efficient Scheduling, Carbon-aware Resource Allocation, Cloud Workload Management, Intelligent Optimization Techniques

1. INTRODUCTION

Cloud computing has become an important technology in the modern digital world. It allows users to access computing resources such as servers, storage systems, software applications, and databases through the internet instead of maintaining physical infrastructure locally. Many sectors, including healthcare, banking, education, industries, and research organizations, use cloud computing because it provides flexibility, scalability, easy accessibility, and cost efficiency. The rapid growth of cloud computing has also increased the size and number of cloud data centers around the world[1]. These data centers operate continuously to process and manage large amounts of data and online services. Since cloud servers run all the time, they consume a huge amount of electricity for computing, storage, networking, and cooling systems. Most electricity generation still depends on fossil fuels such as coal, oil, and natural gas. The burning of these fossil fuels releases carbon dioxide (CO_2) and greenhouse gases into the atmosphere, which contribute to global warming and climate change. As cloud usage continues to increase rapidly, the energy consumption and carbon emissions produced by cloud data centers are also becoming major environmental concerns.

Traditional cloud scheduling and resource management methods mainly focus on improving system performance, response time, execution speed, and resource utilization [2]. In many existing systems, workloads are executed immediately on available servers without considering the environmental impact caused by electricity consumption. However, the carbon intensity of electricity changes depending on the availability of renewable energy sources such as solar and wind power. Therefore, executing workloads during low-carbon periods can help reduce environmental pollution and improve sustainability. To address these environmental challenges, the concept of green cloud computing has emerged. Green cloud computing focuses on reducing energy consumption, minimizing carbon emissions, and improving energy efficiency in cloud environments [3]. Researchers have proposed various energy-efficient and carbon-aware scheduling approaches to improve cloud sustainability while maintaining system performance. Several modern studies also use machine learning, artificial intelligence, workload prediction, and optimization techniques to improve intelligent resource allocation and scheduling decisions. This work examines various existing studies related to energy-efficient and carbon-aware cloud computing systems. The paper discusses different approaches, such as intelligent scheduling, workload prediction, virtualization, dynamic resource allocation, carbon-aware scheduling, and hybrid optimization methods used in green cloud computing environments. Machine learning and optimization techniques such as Long Short-Term Memory (LSTM), Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimization (GWO) discussed in recent studies are also analyzed. The main objective of this review paper is to analyze and compare existing methods used for reducing energy consumption and carbon emissions in cloud data centers. The paper also highlights the advantages, limitations, and challenges of current approaches and emphasizes the importance of developing sustainable and environmentally responsible cloud computing systems for future digital infrastructure.

2. RESEARCH METHODOLOGY

2.1 Datasets

This paper analyzes various existing studies related to energy-efficient and carbon-aware green cloud computing systems. Different research works discussed in this paper use several real-world datasets for workload analysis, energy estimation, carbon intensity monitoring, and intelligent cloud scheduling. These datasets help researchers understand cloud workload behavior, energy consumption patterns, and environmental impact in cloud data centers. One of the most commonly used datasets in green cloud computing research is the Google Cluster Dataset. This dataset contains detailed information about cloud workloads such as CPU utilization, memory usage, task scheduling, task duration, and resource allocation. Researchers use this dataset to study workload fluctuations and predict future resource demand in cloud environments. Since cloud workloads continuously change depending on user requests and application

requirements, workload datasets are important for developing intelligent scheduling and energy management systems.
Another widely used dataset is the UK Carbon Intensity Dataset. This dataset provides information related to electricity generation sources and carbon emission levels over different time periods. It includes carbon intensity values, fossil fuel contribution, and renewable energy usage. Carbon intensity refers to the amount of carbon dioxide produced during electricity generation. Researchers use this dataset to develop carbon-aware scheduling systems that execute workloads during low-carbon periods to reduce environmental impact.
Several studies also use real-time cloud monitoring data, AWS workload statistics, Kubernetes scheduling logs, and container-based workload datasets for analyzing cloud resource management and energy optimization. These datasets help researchers evaluate the performance of intelligent scheduling algorithms and sustainable cloud management techniques.

Table 1: Common Datasets Used in Green Cloud Computing Studies

Dataset Name	Data Type	Description	Purpose
Google Cluster Dataset	Cloud workload data	Contains CPU usage, memory allocation, task scheduling, and workload details	Used for workload analysis and prediction
UK Carbon Intensity Dataset	Carbon emission data	Provides carbon intensity values and renewable energy information	Used for carbon-aware scheduling
AWS Cloud Monitoring Data	Cloud infrastructure data	Contains resource usage and workload monitoring information	Used for energy-efficient cloud management
Kubernetes Scheduling Logs	Container scheduling data	Contains container workload allocation details	Used for intelligent workload scheduling
Real-Time Energy Consumption Data	Energy usage data	Monitors server energy consumption and power utilization	Used for energy estimation and optimization

These datasets provide important information for developing intelligent, energy-efficient, and environmentally sustainable cloud computing systems.

2.2 Data Preprocessing

Data preprocessing plays an important role in green cloud computing research because cloud and energy datasets often contain missing values, noisy records, duplicate entries, and inconsistent formats. Using raw data directly may reduce the accuracy and efficiency of machine learning models and optimization algorithms. Therefore, many existing studies apply preprocessing techniques to improve data quality before performing workload prediction and scheduling tasks. One of the most common preprocessing steps is data cleaning. During this process, missing values, corrupted records, duplicate entries, and unnecessary information are identified and removed from the datasets. Data cleaning improves consistency and ensures that the machine learning models receive reliable input data. Normalization is another important preprocessing technique used in many studies. Cloud workload features such as CPU utilization, memory allocation, and carbon intensity values may exist in different numerical ranges. Normalization scales feature values into a common range and improves the performance and stability of prediction models.

Feature extraction and feature selection techniques are also widely used in green cloud computing research. Researchers select important workload and energy-related features such as CPU usage, task duration, memory consumption, renewable energy percentage, and carbon intensity values for analysis. Removing irrelevant or redundant features reduces computational complexity and improves prediction accuracy. Several studies also convert workload data into time-series format because cloud workloads continuously change over time. Time-series transformation helps machine learning models identify workload patterns and predict future resource demand more accurately. Data integration techniques are applied by combining workload datasets with carbon intensity and energy consumption datasets. This integration enables intelligent carbon-aware scheduling and helps cloud systems make environmentally responsible workload allocation decisions.

Table 2: Preprocessing Techniques Used in Green Cloud Computing Studies

Preprocessing Technique	Purpose	Benefit
Data Cleaning	Remove missing and noisy data	Improves data quality and reliability
Normalization	Scale feature values into a common range	Enhances machine learning performance
Feature Selection	Select important workload and energy features	Reduces complexity and improves accuracy
Time-Series Transformation	Convert workload data into sequential format	Helps workload prediction
Data Integration	Combine workload and carbon datasets	Supports carbon-aware scheduling

Proper preprocessing improves the efficiency, reliability, and accuracy of intelligent green cloud computing systems.

2.3 Machine Learning and Optimization Techniques

Machine learning and optimization techniques are widely used in existing green cloud computing studies to improve workload prediction, energy management, intelligent scheduling, and carbon emission reduction. These techniques help cloud systems make efficient scheduling decisions while maintaining system performance and reducing environmental impact. Many studies use Long Short-Term Memory (LSTM) networks for workload prediction. LSTM is a deep learning model designed for time-dependent and sequential data analysis[4]. Since cloud workloads continuously fluctuate over time, LSTM models help predict future workload demand accurately. Accurate workload prediction improves resource allocation and reduces unnecessary energy consumption in cloud environments.

Particle Swarm Optimization (PSO) is another commonly used optimization technique in green cloud computing research[5]. PSO is inspired by the movement behavior of birds and fish schools. Researchers use PSO to optimize workload prediction parameters and improve the performance of scheduling algorithms. Several studies also use Genetic Algorithms (GA) and Grey Wolf Optimization (GWO) for

intelligent scheduling and energy optimization[6]. Genetic Algorithms use concepts such as selection, crossover, and mutation to identify optimal scheduling solutions. Grey Wolf Optimization is inspired by the hunting behavior of grey wolves and helps search for efficient workload scheduling strategies.
Artificial intelligence techniques such as anomaly detection, predictive workload forecasting, and AI-driven resource management are also widely discussed in recent green cloud computing research. Containerization technologies, Kubernetes scheduling, and dynamic workload migration are used to improve scalability and resource utilization in cloud data centers[7]. Researchers also use server power models to estimate energy consumption based on CPU utilization and workload demand. Combining workload prediction with carbon intensity analysis allows intelligent systems to schedule workloads during periods with lower carbon emissions and higher renewable energy availability.

Table 3: Machine Learning and Optimization Techniques Used in Existing Studies

Technique	Purpose	Advantages
LSTM	Predict future cloud workloads	Learns workload patterns accurately
PSO	Optimize workload prediction models	Improves prediction performance
Genetic Algorithm (GA)	Intelligent workload scheduling	Reduces energy consumption
Grey Wolf Optimization (GWO)	Multi-objective scheduling optimization	Balances performance and energy efficiency
AI-Based Scheduling	Intelligent resource management	Improves cloud sustainability
Server Power Models	Estimate energy consumption	Calculates workload energy usage

These machine learning and optimization techniques play an important role in developing sustainable, energy-efficient, and carbon-aware cloud computing systems for future digital infrastructure.

4. COMPARISON OF EXISTING STUDIES

Green cloud computing has become an important research area because modern cloud data centers consume a very large amount of electricity. As the demand for cloud services, artificial intelligence applications, online storage, and digital platforms continues to increase, energy consumption and carbon emissions produced by data centers are also increasing rapidly. Traditional cloud scheduling systems mainly focus on improving performance, reducing execution time, and managing operational costs[8]. However, these approaches often ignore the environmental impact caused by high energy usage and carbon emissions. To solve this problem, many researchers have proposed energy-efficient and carbon-aware cloud computing frameworks. Existing studies focus on different techniques such as workload consolidation, intelligent task scheduling, virtualization, renewable energy integration, carbon-aware workload migration, and AI-based optimization methods. Some studies mainly concentrate on reducing energy consumption, while recent research works also consider real-time carbon intensity and environmental sustainability.
Machine learning and artificial intelligence techniques are now widely used in green cloud computing research[9]. Advanced methods such as workload prediction, dynamic resource allocation, anomaly detection, and hybrid optimization algorithms help improve cloud efficiency and reduce unnecessary power consumption. Real-time carbon intensity analysis also allows cloud systems to schedule workloads

during periods when renewable energy usage is high and carbon emissions are lower. Although many studies have achieved promising results, several challenges still exist[10]. Some frameworks require complex implementation, while others depend heavily on real-time carbon data availability and advanced computational resources. Maintaining system performance while reducing energy consumption and carbon emissions also remains an important challenge in modern cloud environments.
The following table presents a comparison of existing studies related to energy-efficient and carbon-aware green cloud computing systems.

Table 4: Comparison of Existing Studies in Green Cloud Computing

S.No	Study / Approach	Main Focus	Techniques Used	Advantages	Limitations
1	Green Cloud Infrastructure using Energy-Aware Scheduling	Sustainable cloud infrastructure and energy optimization	Dynamic resource provisioning, virtualization, workload consolidation, AI-driven scheduling	Reduces energy consumption and improves sustainability	Focuses mainly on energy efficiency and gives less importance to carbon emissions
2	Hybrid Carbon- and Energy-Aware Scheduling for Green Cloud Computing	Carbon-aware scheduling with service-level management	Carbon-aware scheduling, workload classification, dynamic migration, SLO-aware optimization	Reduces carbon emissions while maintaining cloud performance	Higher scheduling complexity and implementation overhead
3	Green Support System (GSS) Framework for Energy-Efficient Cloud Computing	AI-driven sustainable cloud framework	Predictive workload forecasting, anomaly detection, AI optimization, responsible AI mechanisms	Improves energy efficiency and supports sustainable cloud operations	Requires large computational resources and complex AI integration
4	Cloud-Based Framework for Energy-Efficient Task Scheduling Using Carbon Intensity Data	Real-time carbon-aware workload scheduling	Carbon intensity analysis, Kubernetes scheduling, containerized workload management	Dynamically reduces carbon emissions and operational cost	Depends heavily on real-time carbon intensity data

S.No	Study / Approach	Main Focus	Techniques Used	Advantages	Limitations
5	Proposed Energy and Carbon Efficient Intelligent Scheduling Framework	Intelligent low-carbon cloud scheduling and optimization	LSTM workload prediction, PSO optimization, carbon estimation, GWO and Genetic Algorithm scheduling	Balances energy efficiency, carbon reduction, and cloud performance	Requires accurate prediction models and continuous monitoring
6	Energy-Efficient Task Scheduling in Green Cloud Computing	Intelligent energy-efficient cloud scheduling	AWS services, Kubernetes, containerized workloads, carbon intensity analysis	Improves scalability, reduces energy usage, and supports sustainable cloud environments	Complex integration and workload management in large cloud systems

The comparison of existing studies clearly shows that green cloud computing research is gradually moving from traditional energy-aware systems toward more intelligent and environmentally responsible cloud scheduling frameworks. Earlier research mainly focused on reducing energy consumption through techniques such as virtualization, workload consolidation, and dynamic resource allocation. These methods helped improve resource utilization and reduce unnecessary power usage in cloud data centers.Recent studies have introduced carbon-aware scheduling approaches that consider not only energy consumption but also the environmental impact of electricity generation. Since electricity produced from fossil fuels creates higher carbon emissions, modern frameworks use carbon intensity data to schedule workloads during low-carbon periods. This helps reduce the carbon footprint of cloud systems without affecting cloud performance significantly.

Artificial intelligence and machine learning techniques are also becoming important in modern green cloud computing research. AI-based workload prediction, anomaly detection, and intelligent optimization methods help cloud systems make better scheduling decisions. Hybrid optimization algorithms such as Genetic Algorithms, Grey Wolf Optimization, and Particle Swarm Optimization are used to improve scheduling efficiency, reduce energy consumption, and maintain service quality. Several studies also focus on cloud-native technologies such as Kubernetes scheduling, containerization, and dynamic workload migration. These technologies help improve scalability and support real-time intelligent resource management in large cloud infrastructures.

However, despite the improvements achieved by existing approaches, several challenges still remain. Many frameworks require complex implementation and advanced computational resources. Some methods depend heavily on real-time carbon intensity data availability, which may not always be accessible in all regions. In addition, balancing energy efficiency, carbon reduction, and cloud performance remains a difficult task. The proposed research framework aims to address these limitations by integrating workload prediction, energy estimation, carbon-aware scheduling, and hybrid optimization techniques into a unified intelligent cloud scheduling system. By combining machine learning with carbon-aware decision-making, the framework aims to reduce energy consumption and carbon emissions while maintaining efficient cloud performance and service quality.

4. RESULTS AND DISCUSSION

The analysis of existing studies shows that green cloud computing has become an important research area due to the rapid increase in energy consumption and carbon emissions produced by modern cloud data centers. Many researchers have proposed different energy-efficient and carbon-aware scheduling methods to improve sustainability while maintaining cloud performance and service quality. From the reviewed studies, it is observed that traditional cloud scheduling systems mainly focus on performance metrics such as response time, execution speed, throughput, and resource utilization. Although these approaches improve computational efficiency, they often ignore the environmental impact caused by high electricity consumption and carbon emissions. As a result, recent research has shifted toward green cloud computing approaches that focus on both performance optimization and environmental sustainability.

The reviewed studies show that intelligent workload scheduling plays a major role in reducing energy consumption in cloud environments. Techniques such as workload consolidation, virtualization, dynamic resource allocation, and containerized scheduling help improve resource utilization and reduce unnecessary server power consumption. Several studies also demonstrate that executing workloads during periods of low carbon intensity can significantly reduce the carbon footprint of cloud data centers. Machine learning and artificial intelligence techniques are widely used in recent green cloud computing research. Long Short-Term Memory (LSTM) models are commonly applied for workload prediction because cloud workloads continuously vary over time. Accurate workload prediction helps cloud systems allocate resources more efficiently and avoid unnecessary energy usage. Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Grey Wolf Optimization (GWO) are also used in several studies to improve scheduling efficiency and optimize resource management.

The review also highlights the importance of carbon-aware scheduling techniques. Many existing approaches use real-time carbon intensity data to identify environmentally friendly periods for workload execution. Studies using renewable energy and carbon intensity analysis demonstrate that cloud workloads can be shifted to low-carbon periods without significantly affecting system performance. This helps reduce environmental pollution and supports sustainable cloud infrastructure development. Several reviewed papers also emphasize the use of cloud-native technologies such as Kubernetes scheduling, containerization, workload migration, and dynamic scaling. These technologies improve scalability, flexibility, and intelligent resource management in modern cloud data centers. AI-driven workload forecasting and anomaly detection methods further improve cloud system efficiency and reliability.

Although the reviewed studies achieved promising improvements in energy efficiency and carbon reduction, some limitations still exist. Many approaches require complex implementation and advanced computational resources. Real-time carbon-aware scheduling also depends on the availability of live carbon intensity data. In addition, maintaining a balance between energy efficiency, carbon reduction, workload performance, and service quality remains a major challenge in large-scale cloud environments.

The comparative analysis of existing studies indicates that hybrid machine learning and optimization-based scheduling approaches provide better performance than traditional scheduling methods. Integrating workload prediction, carbon intensity analysis, and intelligent optimization algorithms helps improve energy efficiency and reduce environmental impact more effectively. Overall, the reviewed studies demonstrate that intelligent carbon-aware cloud scheduling can play an important role in building sustainable and environmentally responsible cloud computing systems. The findings also show that combining machine learning, optimization techniques, and renewable energy-aware scheduling strategies can significantly improve the sustainability of future cloud infrastructures.

5. CONCLUSION

Green cloud computing has become an important research area due to the increasing energy consumption and carbon emissions produced by modern cloud data centers. This review paper analyzed various existing studies related to energy-efficient and carbon-aware cloud computing systems. The reviewed studies show that intelligent scheduling, workload prediction, machine learning, and optimization techniques can effectively reduce energy usage and environmental impact while maintaining cloud performance. Techniques such as LSTM, PSO, Genetic Algorithms, and carbon-aware scheduling methods play an important role in improving cloud sustainability. Although several challenges such as implementation complexity and real-time data dependency still exist, green cloud computing provides an effective solution for developing sustainable and environmentally responsible cloud infrastructures in the future.

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