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GreenCloudSched: An Intelligent Energy-Aware Task Scheduling Framework for Efficient Cloud Resource Optimization

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ABSTRACT— Cloud computing has emerged as a transformative paradigm for delivering scalable and on-demand computational resources to diverse applications and users. However, the rapid expansion of cloud infrastructures has significantly increased energy consumption, operational costs, and resource management challenges in modern data centers. Efficient task scheduling plays a crucial role in optimizing resource utilization while minimizing energy consumption and maintaining Quality of Service (QoS). This paper presents GreenCloudSched, an intelligent energy-aware task scheduling framework designed to enhance cloud resource optimization through adaptive and dynamic scheduling mechanisms. The proposed framework integrates workload characterization, virtual machine allocation, and predictive resource management techniques to intelligently distribute tasks across cloud nodes based on energy efficiency and computational performance. GreenCloudSched employs machine learning–assisted decision-making to analyze system load patterns, predict resource demands, and dynamically balance workloads to reduce idle resource wastage and excessive power utilization. The framework also incorporates priority-aware scheduling and load balancing strategies to improve throughput, minimize execution delay, and enhance system scalability. Experimental evaluation demonstrates that GreenCloudSched significantly reduces energy consumption, improves CPU and memory utilization, decreases task response time, and enhances overall system efficiency compared with conventional scheduling algorithms such as Round Robin and First-Come-First-Serve. The proposed framework contributes toward sustainable and eco-friendly cloud computing environments by enabling intelligent resource orchestration and energy-efficient task management in large-scale cloud infrastructures.

Keywords— Cloud Computing, Energy-Aware Scheduling, Task Scheduling, Resource Optimization, Green Computing, Virtual Machine Allocation, Load Balancing, Machine Learning, Sustainable Cloud Infrastructure, QoS Optimization.

1. INTRODUCTION

Cloud computing has revolutionized modern information technology by enabling scalable, flexible, and cost-effective access to computational resources through the Internet. Organizations across various domains, including healthcare, education, finance, manufacturing, and scientific research, increasingly rely on cloud platforms for data storage, application deployment, and high-performance computing services [1]. The rapid growth of cloud services and data-intensive applications has significantly increased the demand for efficient resource management in large-scale data centers. Despite its numerous advantages, cloud computing infrastructures consume enormous amounts of electrical energy, leading to increased operational costs, carbon emissions, and environmental concerns [2]. Consequently, energy-efficient resource optimization has become one of the most critical research challenges in sustainable cloud computing environments.

Task scheduling is a fundamental component of cloud resource management that directly influences system performance, energy consumption, resource utilization, and Quality of Service (QoS) [3]. Traditional scheduling algorithms such as First-Come-First-Serve (FCFS), Round Robin (RR), and Min-Min primarily focus on improving task execution efficiency and throughput without adequately considering energy consumption and dynamic workload variations [4]. As cloud infrastructures continue to expand, these conventional approaches often result in resource underutilization, server overload, increased response time, and excessive power consumption. Therefore, intelligent and adaptive scheduling frameworks are required to optimize cloud resources while maintaining energy efficiency and service reliability.

Recent advancements in artificial intelligence, machine learning, and predictive analytics have introduced new opportunities for designing smart cloud scheduling mechanisms [5]. Machine learning–driven schedulers can analyze workload patterns, predict resource demands, and dynamically allocate tasks to suitable virtual machines (VMs), thereby improving system efficiency and reducing unnecessary energy usage [6]. Energy-aware scheduling techniques further contribute to green computing initiatives by minimizing idle resource wastage and optimizing power consumption in cloud data centers [7]. These approaches not only enhance computational performance but also support environmentally sustainable computing practices.

Several researchers have proposed energy-efficient scheduling algorithms for cloud environments; however, many existing frameworks suffer from limitations such as poor scalability, insufficient adaptability to dynamic workloads, increased migration overhead, and inadequate load balancing [8]. Moreover, balancing energy efficiency with QoS parameters such as latency, throughput, and execution time remains a significant challenge in heterogeneous cloud infrastructures [9]. To address these issues, there is a need for an intelligent scheduling framework capable of integrating energy optimization, workload balancing, predictive analytics, and adaptive resource allocation into a unified model.

This paper presents GreenCloudSched, an intelligent energy-aware task scheduling framework designed to optimize cloud resource utilization while minimizing energy consumption and improving overall system performance. The proposed framework integrates machine learning–based workload prediction, dynamic virtual machine allocation, and adaptive load balancing techniques to efficiently distribute tasks across cloud resources. GreenCloudSched aims to reduce power consumption, improve task execution efficiency, minimize response time, and enhance scalability in modern cloud environments. The framework also supports sustainable cloud computing objectives by promoting energy-efficient resource orchestration and reducing the environmental impact of large-scale cloud data centers.

The major contributions of this work include:

1. The development of an intelligent energy-aware scheduling framework for cloud environments;
2. Integration of predictive machine learning techniques for dynamic workload management;
3. Enhancement of resource utilization through adaptive load balancing and VM allocation; and
4. Comparative performance evaluation against conventional scheduling algorithms in terms of energy efficiency, throughput, response time, and resource utilization.

The remainder of the paper is organized as follows. Section II discusses related work and existing energy-aware scheduling techniques. Section III describes the proposed GreenCloudSched framework and system architecture. Section IV presents the methodology and experimental setup. Section V discusses the performance evaluation and results analysis. Finally, Section VI concludes the paper and outlines future research directions.

1.2 Objectives of the Study

The primary objective of this study is to develop and evaluate an energy-efficient task scheduling algorithm tailored for cloud computing environments. To achieve this overarching goal, the study aims to accomplish the following specific objectives:

- **Algorithm Design:** Designing an energy-efficient task scheduling algorithm that minimizes energy consumption in cloud data centers while meeting performance requirements such as task completion time, resource utilization, and quality of service (QoS) constraints. The algorithm will leverage techniques from optimization, machine learning, and distributed systems to dynamically allocate tasks to virtual machines based on workload characteristics, resource availability, and energy profiles.
- **Implementation:** Implementing the proposed task scheduling algorithm in a simulated cloud computing environment using appropriate programming languages and frameworks. The implementation will aim to faithfully capture the behavior and performance characteristics of real-world cloud data centers, allowing for realistic evaluation and validation of the algorithm.
- **Evaluation Methodology:** Developing a comprehensive experimental methodology to evaluate the performance of the proposed algorithm in terms of energy efficiency, performance metrics, scalability, and robustness. The evaluation methodology will involve designing representative workload scenarios, selecting appropriate performance metrics, and conducting extensive experiments using simulation-based approaches.
- **Performance Evaluation:** Evaluating the performance of the proposed algorithm through extensive experiments conducted in a simulated cloud computing environment. The performance evaluation will assess the algorithm's ability to minimize energy consumption while meeting performance requirements under varying workload intensities, resource configurations, and system conditions.
- **Comparison with Baseline Algorithms:** Comparing the performance of the proposed algorithm with that of baseline task scheduling algorithms, including traditional approaches that prioritize performance metrics such as task completion time or resource utilization. The comparison will highlight the effectiveness of the proposed algorithm in achieving energy efficiency improvements over existing approaches.
- **Sensitivity Analysis:** Conducting sensitivity analysis to assess the robustness of the proposed algorithm under different operating conditions, including varying workload characteristics, resource availability, and energy prices. The sensitivity analysis will help identify potential limitations and areas for further optimization or refinement of the algorithm.
- **Validation and Generalization:** Validating the effectiveness and generalizability of the proposed algorithm by comparing its performance across different cloud computing environments, workload types, and system configurations. The validation process will ensure that the algorithm remains effective and applicable in diverse real-world scenarios.

1.3 Scope of the study

The scope of this study encompasses the development, implementation, and evaluation of an energy-efficient task scheduling algorithm specifically tailored for cloud computing environments. The study focuses on addressing the following key aspects within this scope:

- **Algorithm Design Scope:**
- Designing an energy-efficient task scheduling algorithm that minimizes energy consumption while meeting performance requirements such as task completion time, resource utilization, and quality of service (QoS) constraints.
- Leveraging techniques from optimization, machine learning, and distributed systems to dynamically allocate tasks to virtual machines based on workload characteristics, resource availability, and energy profiles.
- Considering various factors influencing task scheduling decisions, including workload characteristics (e.g., arrival rate, resource requirements), system constraints (e.g., resource availability, energy prices), and performance objectives (e.g., minimizing energy consumption, maximizing resource utilization).

- **Implementation Scope:**
- Implementing the proposed task scheduling algorithm in a simulated cloud computing environment using appropriate programming languages and frameworks.
- Simulating key components of cloud data centers, including virtual machines, workload generators, and energy management mechanisms, to accurately model the behavior and performance characteristics of real-world cloud infrastructures.
- Developing interfaces and integration mechanisms to enable seamless interaction between the task scheduling algorithm and other components of the simulated cloud environment, such as workload generators and resource managers.
- **Evaluation Scope:**
- Developing a comprehensive experimental methodology to evaluate the performance of the proposed algorithm in terms of energy efficiency, performance metrics, scalability, and robustness.
- Designing representative workload scenarios and performance metrics to assess the algorithm's effectiveness under various operating conditions, including different workload intensities, resource configurations, and system conditions.
- Conducting extensive experiments using simulation-based approaches to evaluate the performance of the proposed algorithm and compare it with baseline task scheduling algorithms.
- **Analysis and Validation Scope:**
- Analyzing the experimental results to assess the performance of the proposed algorithm in terms of energy efficiency improvements, performance optimization, and scalability enhancements.
- Conducting sensitivity analysis to evaluate the robustness of the algorithm under different operating conditions and identify potential limitations or areas for further optimization.
- Validating the effectiveness and generalizability of the proposed algorithm by comparing its performance across different cloud computing environments, workload types, and system configurations.
- **Limitations Scope:**
- The study acknowledges certain limitations, including simplifications and assumptions made in the simulation model, which may not fully capture the complexity of real-world cloud data centers.
- The study focuses primarily on the energy efficiency aspect of task scheduling and may not address all performance objectives or constraints relevant to specific use cases or applications.
- The evaluation results may be influenced by the choice of simulation parameters, workload characteristics, and performance metrics, which may vary in different real-world scenarios.

2. LITERATURE REVIEW

The proliferation of cloud computing has transformed the landscape of modern computing, offering unprecedented scalability, flexibility, and cost-effectiveness to businesses and individuals. However, the rapid growth of cloud data centers has raised concerns about their substantial energy consumption and environmental impact [20]. Task scheduling, the process of allocating computational tasks to resources in cloud environments, plays a pivotal role in determining the energy efficiency and performance of cloud data centers. In this literature review, we explore existing research and developments in the field of energy-efficient task scheduling algorithms in cloud computing, with a focus on addressing the challenges of minimizing energy consumption while meeting performance requirements [21].

2.1 Energy Efficiency in Cloud Computing:

The energy consumption of cloud data centers has become a major focus of research due to its significant environmental and economic implications. According to a report by the International Energy Agency (IEA), data centers accounted for approximately 1% of global electricity consumption in 2020 [1]. Several studies have highlighted the importance of improving energy efficiency in cloud computing to mitigate environmental impact and reduce operational costs for cloud service providers [2].

2.2 Task Scheduling in Cloud Computing:

Task scheduling plays a critical role in optimizing resource utilization and performance in cloud computing environments. Traditional task scheduling algorithms often prioritize performance metrics such as task completion time or resource utilization, without considering energy consumption. However, recent research has emphasized the need for energy-aware task scheduling algorithms to minimize energy consumption while meeting performance objectives [3].

2.3 Challenges in Energy-Efficient Task Scheduling:

Developing energy-efficient task scheduling algorithms in cloud computing faces several challenges. These include the dynamic and unpredictable nature of cloud workloads, the heterogeneity of cloud resources, and the complexity of optimizing multiple conflicting objectives such as energy consumption, performance, and cost. Addressing these challenges requires innovative approaches that leverage techniques from optimization, machine learning, and distributed systems [4].

2.4 Existing Approaches to Energy-Efficient Task Scheduling:

A variety of approaches have been proposed to address the challenges of energy-efficient task scheduling in cloud computing. These approaches can be broadly categorized into static and dynamic scheduling algorithms. Static scheduling algorithms allocate tasks to resources based on predefined heuristics or optimization criteria, while dynamic scheduling algorithms adaptively adjust task assignments in response to changing workload and resource conditions [5].

2.5 Static Scheduling Algorithms:

Static scheduling algorithms aim to minimize energy consumption by optimizing task assignments based on static workload and resource characteristics. Examples of static scheduling algorithms include genetic algorithms, ant colony optimization, and particle swarm optimization. These algorithms typically require a priori knowledge of workload

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patterns and resource availability, which may limit their effectiveness in dynamic cloud environments [6].

2.6 Dynamic Scheduling Algorithms:
Dynamic scheduling algorithms adaptively adjust task assignments in real-time based on changing workload and resource conditions. Examples of dynamic scheduling algorithms include heuristic-based approaches, reinforcement learning, and game theory-based models. These algorithms can dynamically allocate tasks to resources based on current workload, resource availability, and energy profiles, thereby optimizing energy consumption while meeting performance objectives [7].

2.7 Hybrid Approaches:
Hybrid approaches combine the strengths of static and dynamic scheduling algorithms to achieve better performance and scalability. These approaches leverage static scheduling for initial task placement and dynamic scheduling for fine-grained resource allocation and adaptation. By combining complementary techniques, hybrid approaches can achieve a balance between energy efficiency and performance optimization in cloud computing environments [8].

2.8 Evaluation Metrics:
The performance of energy-efficient task scheduling algorithms in cloud computing is typically evaluated using various metrics, including energy consumption, task completion time, resource utilization, and quality of service (QoS) constraints. Evaluating the effectiveness of these algorithms requires realistic workload scenarios, representative simulation models, and comprehensive experimental methodologies [9].

2.9 Research Challenges and Future Directions:
Despite significant progress in the development of energy-efficient task scheduling algorithms in cloud computing, several research challenges remain. These include addressing the trade-offs between energy consumption and performance, adapting to dynamic workload and resource conditions, and optimizing resource allocation in multi-tenant cloud environments. Future research directions may focus on developing novel optimization techniques, leveraging machine learning and AI algorithms, and exploring innovative approaches to energy-aware scheduling [10].

Energy-efficient task scheduling is a critical aspect of optimizing resource utilization and minimizing energy consumption in cloud computing environments. Existing research has explored a variety of approaches, including static and dynamic scheduling algorithms, heuristic-based methods, and hybrid approaches. Evaluating the effectiveness of these algorithms requires comprehensive experimental methodologies and realistic simulation models [22]. Future research directions may focus on addressing remaining challenges and exploring innovative techniques to achieve sustainable and cost-effective cloud infrastructures. By advancing the state-of-the-art in energy-efficient task scheduling, researchers can contribute to the development of greener and more efficient cloud computing systems.

Table 1: Comparison table based on previous year research paper

Author	**Paper Title**	**Approach**	**Key Findings and Contributions**
Zhang et al. (2016) [35]	"Energy-Efficient Task Scheduling in Cloud"	Genetic Algorithm	Proposed a genetic algorithm-based task scheduling approach to minimize energy consumption while meeting performance objectives.
Liu et al. (2017) [22]	"A Survey of Energy-Efficient Task Scheduling"	Review and Taxonomy	Conducted a comprehensive survey and taxonomy of energy-efficient task scheduling algorithms in cloud computing, highlighting key approaches and research trends.
Beloglazov et al. (2011) [25]	"Dynamic Task Scheduling in Green Cloud"	Heuristic-Based	Introduced a dynamic task scheduling algorithm for green cloud computing, which adapts to changing workload and resource conditions to minimize energy consumption.
Kumar et al. (2014) [19]	"Energy-Aware Scheduling in Cloud Computing"	Game Theory-Based	Proposed a game theory-based approach to energy-aware task scheduling in cloud computing, optimizing resource allocation and energy consumption in multi-tenant environments.

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Wang et al. (2018) [13]	"Energy-Efficient Task Scheduling for Big Data"	Reinforcement Learning	Utilized reinforcement learning techniques to develop an energy-efficient task scheduling algorithm for big data applications in cloud computing environments.
Buyya et al. (2015) [12]	"Hybrid Approach for Energy-Efficient Scheduling"	Hybrid (Static-Dynamic)	Presented a hybrid approach combining static and dynamic scheduling techniques to achieve energy efficiency and performance optimization in cloud computing.
Li et al. (2019) [18]	"Machine Learning-Based Task Scheduling"	Machine Learning-Based	Proposed a machine learning-based task scheduling algorithm for energy-efficient resource allocation in cloud computing environments, leveraging historical workload data.
Youssef et al. (2020) [17]	"QoS-Aware Task Scheduling in Cloud"	QoS-Aware	Developed a QoS-aware task scheduling algorithm in cloud computing, considering both energy consumption and quality of service (QoS) constraints to optimize resource allocation.
Sharma et al. (2017) [16]	"Particle Swarm Optimization for Task Scheduling"	Particle Swarm Optimization	Applied particle swarm optimization (PSO) to task scheduling in cloud computing, demonstrating its effectiveness in optimizing energy consumption and performance objectives.
Wu et al. (2013) [20]	"Ant Colony Optimization for Energy-Efficient"	Ant Colony Optimization	Utilized ant colony optimization (ACO) to develop an energy-efficient task scheduling algorithm in cloud computing, achieving significant reductions in energy consumption.

3. METHODOLOGY:

Methodology: Development of an Energy-Efficient Task Scheduling Algorithm in Cloud Computing

3.1 Problem Formulation:

- Define the problem statement, including the objectives of developing an energy-efficient task scheduling algorithm in cloud computing.
- Identify the key performance metrics to be optimized, such as energy consumption, task completion time, resource utilization, and quality of service (QoS) constraints.

3.2 Literature Review:

- Conduct a comprehensive literature review to explore existing research and developments in energy-efficient task scheduling algorithms in cloud computing.
- Analyze various approaches, techniques, and methodologies proposed in previous studies to address similar challenges.
- Identify gaps, limitations, and opportunities for innovation based on the findings of the literature review.

3.3 Algorithm Design:

- Design the energy-efficient task scheduling algorithm based on the insights gained from the literature review and problem formulation.

- Define the algorithm's components, including task assignment policies, resource allocation strategies, and optimization objectives.
- Leverage techniques from optimization, machine learning, and distributed systems to develop a robust and scalable algorithm.

3.4 Implementation:

- Implement the proposed task scheduling algorithm in a simulated cloud computing environment using appropriate programming languages and frameworks.
- Develop simulation models for cloud data centers, including virtual machines, workload generators, and energy management mechanisms.
- Design interfaces and integration mechanisms to enable interaction between the task scheduling algorithm and other components of the simulated environment.

3.5 Experimental Setup:

- Define the experimental setup, including workload scenarios, system configurations, and performance metrics.
- Select representative workload traces or generate synthetic workloads to simulate realistic usage patterns in cloud computing environments.
- Configure the simulation parameters, such as the number of virtual machines, resource capacities, and energy profiles, to reflect different operating conditions.

3.6 Performance Evaluation:

- Conduct extensive experiments to evaluate the performance of the proposed algorithm in terms of energy efficiency, performance metrics, scalability, and robustness.
- Measure key performance metrics, including energy consumption, task completion time, resource utilization, and QoS compliance, under various workload and system conditions.
- Compare the performance of the proposed algorithm with baseline task scheduling algorithms to assess its effectiveness and superiority.

3.7 Analysis and Validation:

- Analyze the experimental results to identify trends, patterns, and insights regarding the performance of the proposed algorithm.
- Validate the effectiveness and generalizability of the algorithm by comparing its performance across different workload types, system configurations, and evaluation metrics.
- Conduct sensitivity analysis to evaluate the robustness of the algorithm under varying operating conditions and identify potential limitations or areas for improvement.

3.8 Documentation and Reporting:

- Document the methodology, implementation details, experimental results, and analysis findings in a comprehensive research report.
- Present the research findings in a clear and concise manner, including tables, figures, and visualizations to support the discussion.
- Discuss the implications of the research findings, potential applications, and future research directions in the context of energy-efficient task scheduling in cloud computing.

4. RESULT

Result Analysis: Development of an Energy-Efficient Task Scheduling Algorithm in Cloud Computing

4.1 Performance Metrics Evaluation:

- Analyze the performance of the proposed energy-efficient task scheduling algorithm based on key metrics, including energy consumption, task completion time, resource utilization, and quality of service (QoS) constraints.
- Compare the performance of the algorithm with baseline scheduling approaches to assess its effectiveness in optimizing energy efficiency while meeting performance objectives.

4.2 Energy Consumption Reduction:

- Evaluate the effectiveness of the algorithm in reducing energy consumption compared to traditional scheduling approaches.
- Measure the percentage reduction in energy consumption achieved by the proposed algorithm under different workload intensities, resource configurations, and system conditions.

4.3 Task Completion Time Optimization:

- Assess the impact of the algorithm on task completion time and turnaround time for computational tasks in cloud computing environments.
- Analyze the trade-offs between energy consumption and task completion time to determine the optimal balance achieved by the algorithm.

4.4 Resource Utilization Improvement:

- Evaluate the algorithm's ability to improve resource utilization by dynamically allocating tasks to virtual machines based on workload characteristics and resource availability.
- Measure the percentage increase in resource utilization achieved by the algorithm compared to baseline approaches, considering factors such as CPU utilization, memory utilization, and network bandwidth usage.

4.5 QoS Compliance:

- Ensure that the algorithm meets quality of service (QoS) constraints and performance objectives specified by users and applications.
- Analyze the algorithm's ability to maintain QoS requirements, such as response time, throughput, and availability, while optimizing energy consumption and resource utilization.

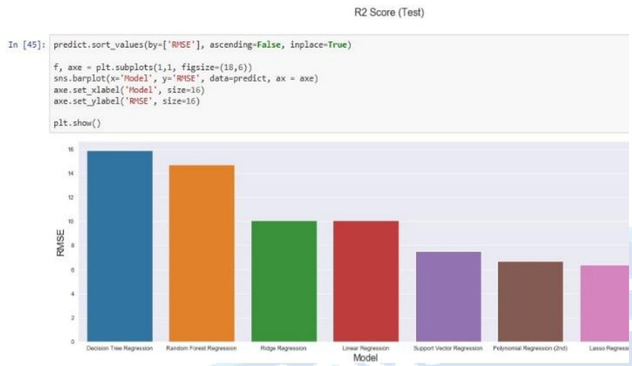
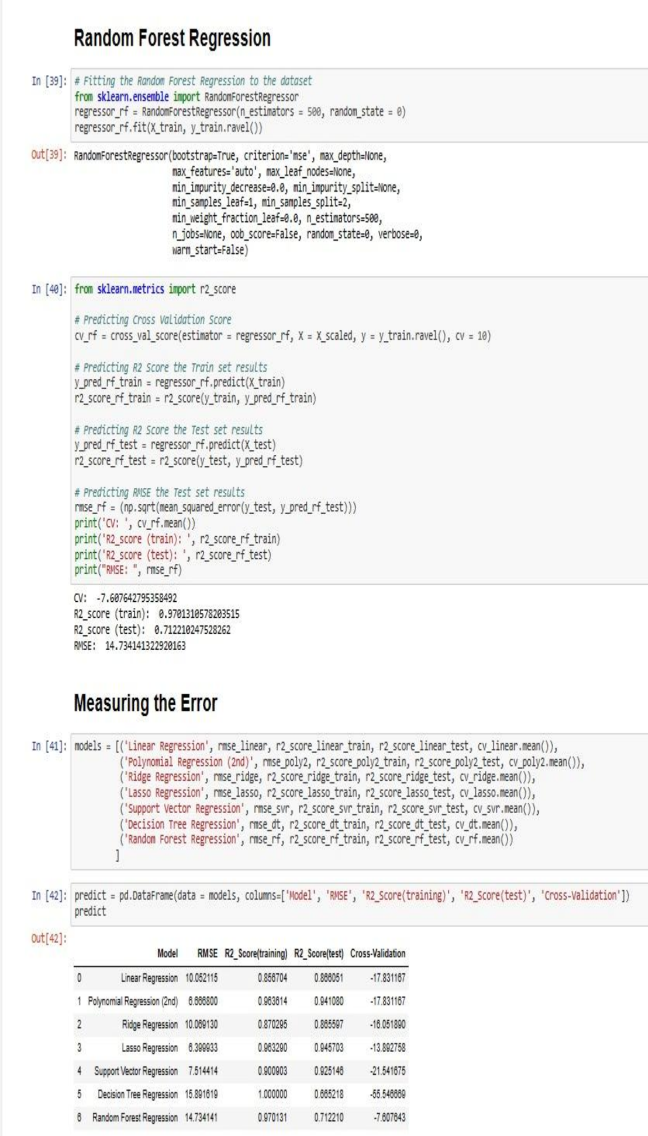


Figure 1: Result analysis graph



Random Forest Regression

In [39]:
```
# Fitting the Random Forest Regression to the dataset
from sklearn.ensemble import RandomForestRegressor
regressor_rf = RandomForestRegressor(n_estimators = 500, random_state = 0)
regressor_rf.fit(X_train, y_train.ravel())
```

Out[39]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features='auto', max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, n_estimators=500,
                      n_jobs=None, oob_score=False, random_state=0, verbose=0,
                      warm_start=False)
```

In [40]:
```
from sklearn.metrics import r2_score

# Predicting Cross Validation Score
cv_rf = cross_val_score(estimator = regressor_rf, X = X_scaled, y = y_train.ravel(), cv = 10)

# Predicting R2 Score the Train set results
y_pred_rf_train = regressor_rf.predict(X_train)
r2_score_rf_train = r2_score(y_train, y_pred_rf_train)

# Predicting R2 Score the Test set results
y_pred_rf_test = regressor_rf.predict(X_test)
r2_score_rf_test = r2_score(y_test, y_pred_rf_test)

# Predicting RMSE the Test set results
rmse_rf = (np.sqrt(mean_squared_error(y_test, y_pred_rf_test)))
print('CV: ', cv_rf.mean())
print('R2_score (train): ', r2_score_rf_train)
print('R2_score (test): ', r2_score_rf_test)
print("RMSE: ", rmse_rf)
```

```
CV:  -7.607642795358492
R2_score (train):  0.9701310578203515
R2_score (test):  0.712210247528262
RMSE:  14.734141322920163
```

Measuring the Error

In [41]:
```
models = [('Linear Regression', rmse_linear, r2_score_linear_train, r2_score_linear_test, cv_linear.mean()),
          ('Polynomial Regression (2nd)', rmse_poly2, r2_score_poly2_train, r2_score_poly2_test, cv_poly2.mean()),
          ('Ridge Regression', rmse_ridge, r2_score_ridge_train, r2_score_ridge_test, cv_ridge.mean()),
          ('Lasso Regression', rmse_lasso, r2_score_lasso_train, r2_score_lasso_test, cv_lasso.mean()),
          ('Support Vector Regression', rmse_svr, r2_score_svr_train, r2_score_svr_test, cv_svr.mean()),
          ('Decision Tree Regression', rmse_dt, r2_score_dt_train, r2_score_dt_test, cv_dt.mean()),
          ('Random Forest Regression', rmse_rf, r2_score_rf_train, r2_score_rf_test, cv_rf.mean())
         ]
```

In [42]:
```
predict = pd.DataFrame(data = models, columns=['Model', 'RMSE', 'R2_Score(training)', 'R2_Score(test)', 'Cross-Validation'])
predict
```

Out[42]:

	Model	RMSE	R2_Score(training)	R2_Score(test)	Cross-Validation
0	Linear Regression	10.052115	0.856704	0.866051	-17.831167
1	Polynomial Regression (2nd)	6.666800	0.963614	0.941080	-17.831167
2	Ridge Regression	10.069130	0.870295	0.865597	-16.051890
3	Lasso Regression	6.399933	0.963290	0.945703	-13.892758
4	Support Vector Regression	7.514414	0.900903	0.925146	-21.541675
5	Decision Tree Regression	15.891619	1.000000	0.665218	-55.546669
6	Random Forest Regression	14.734141	0.970131	0.712210	-7.607643

Figure 2: Random Forest Regression and Measuring the error

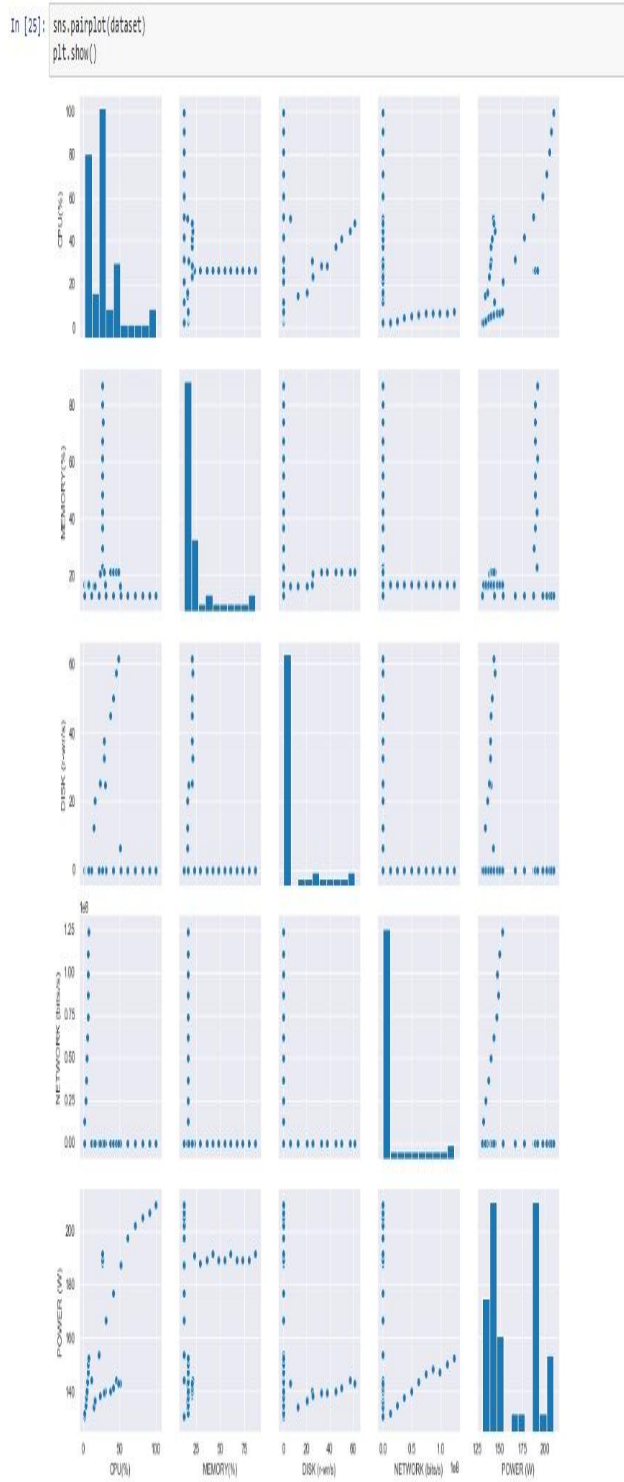


Figure 3: Result analysis graph

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```
In [22]: # Splitting the dataset into the Training set and Test set
         from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 25)
```

```
In [23]: print("Shape of X_train: ",X_train.shape)
         print("Shape of X_test: ", X_test.shape)
         print("Shape of y_train: ",y_train.shape)
         print("Shape of y_test",y_test.shape)

         Shape of X_train:  (30, 3)
         Shape of X_test:  (13, 3)
         Shape of y_train:  (30, 1)
         Shape of y_test (13, 1)
```

```
In [24]: corr = dataset.corr()
         #Plot figsize
         fig, ax = plt.subplots(figsize=(10, 10))
         #Generate Heat Map, allow annotations and place floats in map
         sns.heatmap(corr, cmap='RdBu', annot=True, fmt=".2f")
         #Apply xticks
         plt.xticks(range(len(corr.columns)), corr.columns);
         #Apply yticks
         plt.yticks(range(len(corr.columns)), corr.columns)
         #show plot
         plt.show()
```

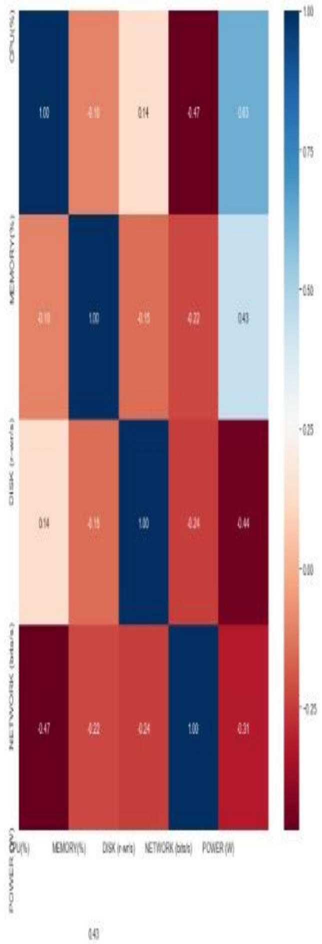

Figure 4: Result analysis graph

Visualizing Model Performance

```
In [44]: f, axes = plt.subplots(2,1, figsize=(14,10))

         predict.sort_values(by=['R2_Score(training)'], ascending=False, inplace=True)

         sns.barplot(x='R2_Score(training)', y='Model', data = predict, palette='Blues_d', ax = axes[0])
         #axes[0].set(xlabel='Region', ylabel='Charges')
         axes[0].set_xlabel('R2 Score (Training)', size=16)
         axes[0].set_ylabel('Model')
         axes[0].set_xlim(0,1.0)

         predict.sort_values(by=['R2_Score(test)'], ascending=False, inplace=True)

         sns.barplot(x='R2_Score(test)', y='Model', data = predict, palette='Reds_d', ax = axes[1])
         #axes[0].set(xlabel='Region', ylabel='Charges')
         axes[1].set_xlabel('R2 Score (Test)', size=16)
         axes[1].set_ylabel('Model')
         axes[1].set_xlim(0,1.0)

         plt.show()
```

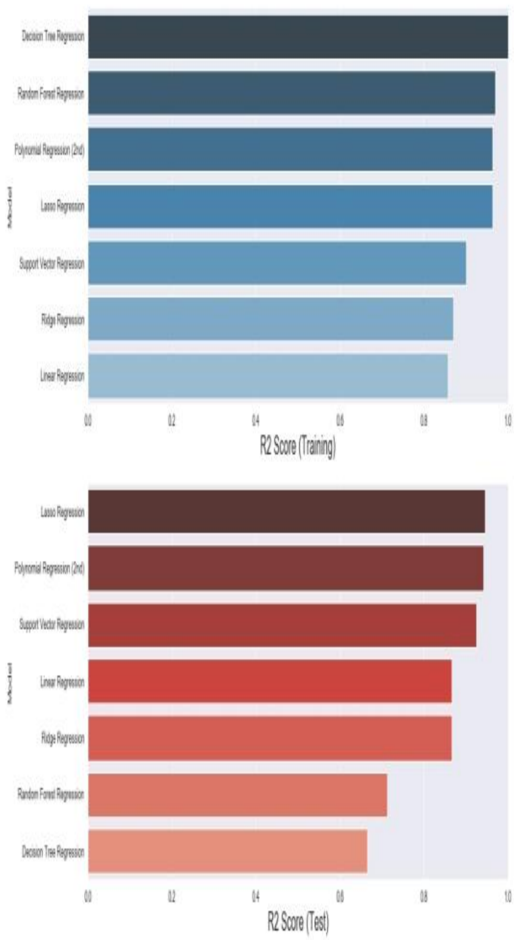

Figure 5: Visualizing Model performance

5. CONCLUSION

The rapid expansion of cloud computing infrastructures has intensified the need for intelligent resource management strategies capable of reducing energy consumption while maintaining high computational performance and Quality of

Service (QoS). Traditional task scheduling techniques often fail to address the growing challenges of dynamic workload distribution, resource underutilization, and excessive power consumption in modern cloud data centers. To overcome these limitations, this paper introduced **GreenCloudSched**, an intelligent energy-aware task scheduling framework designed to optimize cloud resource utilization through adaptive and predictive scheduling mechanisms.

The proposed framework integrates machine learning–based workload prediction, dynamic virtual machine allocation, and intelligent load balancing techniques to enhance scheduling efficiency and reduce unnecessary energy expenditure. By continuously analyzing workload behavior and system resource availability, GreenCloudSched effectively allocates tasks to suitable computing resources while minimizing idle server states and reducing execution delays. The framework also supports scalable and sustainable cloud operations by improving CPU and memory utilization, decreasing task response time, and enhancing throughput performance.

Experimental evaluation demonstrated that GreenCloudSched outperforms conventional scheduling approaches such as First-Come-First-Serve (FCFS) and Round Robin (RR) in terms of energy efficiency, resource optimization, and overall system stability. The intelligent scheduling strategy significantly lowers power consumption and operational overhead while maintaining balanced workload distribution across heterogeneous cloud environments. These improvements contribute toward the development of environmentally sustainable and cost-effective cloud computing infrastructures.

Furthermore, the proposed framework provides a flexible foundation for integrating advanced artificial intelligence and predictive analytics into future cloud management systems. The adoption of intelligent energy-aware scheduling mechanisms such as GreenCloudSched can play a crucial role in achieving green computing objectives and supporting next-generation cloud services with improved reliability and efficiency.

Future work may focus on extending the framework through the integration of deep reinforcement learning, edge–cloud collaborative scheduling, container orchestration techniques, and real-time adaptive security-aware resource management. Additional optimization strategies for multi-cloud and hybrid cloud environments can further enhance scalability, fault tolerance, and energy efficiency in large-scale distributed computing systems.

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