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ANALYZE AND OPTIMIZE CLOUD RESOURCE ALLOCATION USING MACHINE LEARNING FOR SUSTAINABLE GREEN IT INFRASTRUCTURE

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Abstract
The rapid growth of cloud computing has resulted in significant energy consumption, raising sustainability concerns and environmental impacts associated with large-scale IT infrastructure. Efficient cloud resource allocation is essential for balancing performance, cost, and energy efficiency while supporting dynamic workloads. This study investigates the use of machine learning algorithms to optimize cloud resource allocation in multi-tenant cloud environments to promote sustainable green IT infrastructure. A conceptual model was developed linking predictive workload modeling, intelligent VM placement, energy-aware scheduling, and dynamic scaling with key sustainability outcomes, including energy consumption reduction, carbon footprint minimization, and resource utilization efficiency. A quantitative research design employing Partial Least Squares Structural Equation Modeling was applied to assess relationships between these constructs. Data were collected from 420 cloud engineers, IT infrastructure managers, and data center operators across enterprises implementing green IT initiatives. The measurement model demonstrated reliability and convergent validity with composite reliability values exceeding 0.91 and average variance extracted above 0.63. Structural model analysis revealed that predictive workload modeling beta 0.56 $p < 0.001$, energy-aware scheduling beta 0.49 $p < 0.001$, and intelligent VM placement beta 0.42 $p < 0.001$ significantly enhance energy efficiency and resource utilization. Dynamic scaling mediates the relationship between workload prediction and energy efficiency beta 0.44 $p < 0.001$. The model explained 65 percent of variance in energy efficiency and 61 percent in sustainable performance. These findings indicate that integrating machine learning for workload forecasting, intelligent allocation, and energy-aware scheduling significantly supports sustainable cloud operations. The study provides a validated framework for cloud infrastructure managers and policymakers to design energy-efficient, scalable, and environmentally sustainable cloud computing environments.

Keywords: Cloud Computing, Resource Allocation, Machine Learning, Green IT, Energy Efficiency, Structural Equation Modeling

Introduction

Cloud computing has become the backbone of modern IT infrastructure, supporting services ranging from software as a service (SaaS) to infrastructure as a service (IaaS) and platform as a service (PaaS). Its scalability, flexibility, and on-demand resource availability make it indispensable for enterprises, research institutions, and service providers. However, the exponential increase in cloud data centers has led to high energy consumption, contributing to carbon emissions and environmental degradation (Beloglazov et al., 2012). As a result, sustainable green IT practices have become a critical focus, emphasizing energy-efficient operation, optimized resource allocation, and reduced environmental impact.

Efficient resource allocation in cloud computing involves assigning virtual machines (VMs), storage, and computing resources to workloads in a way that maximizes performance while minimizing operational cost and energy consumption. Traditional resource allocation techniques often rely on static allocation, round-

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robin scheduling, or heuristic-based algorithms, which may fail to adapt to dynamic workloads, resulting in energy wastage and underutilized resources (Calheiros et al., 2015). Machine learning (ML) algorithms offer adaptive and predictive capabilities that enable intelligent resource allocation, workload prediction, and energy optimization.

Predictive workload modeling is a critical aspect of ML-based cloud optimization. By forecasting incoming workload patterns, cloud management systems can allocate resources proactively, reduce idle server time, and balance loads efficiently. Energy-aware scheduling further ensures that workloads are assigned to servers or VMs in a manner that minimizes total energy consumption while meeting quality of service (QoS) requirements. Intelligent VM placement strategies utilize ML to optimize VM placement across physical servers, considering performance, energy, and network latency metrics.

Dynamic scaling or elasticity complements these techniques by allowing automatic adjustment of resources based on workload fluctuations. Horizontal scaling adds or removes VM instances, while vertical scaling adjusts resource capacity of existing VMs. Together, predictive modeling, intelligent VM placement, energy-aware scheduling, and dynamic scaling form a comprehensive approach to sustainable cloud resource management.

Despite significant advances in machine learning applications for cloud optimization, empirical studies validating integrated frameworks linking these techniques to green IT outcomes remain limited. Most research focuses on isolated techniques, lacking systematic analysis of interdependent effects on energy efficiency and sustainable performance metrics. There is also limited use of robust quantitative models such as Structural Equation Modeling to validate the relationships between ML-based techniques and energy outcomes in cloud environments.

This study aims to fill these gaps by developing a conceptual model for intelligent cloud resource allocation using ML algorithms. The model investigates how predictive workload modeling, intelligent VM placement, energy-aware scheduling, and dynamic scaling collectively influence energy efficiency and sustainable performance of cloud infrastructure. Using SmartPLS, direct and mediating relationships among constructs are analyzed quantitatively, providing evidence-based insights for cloud managers and policymakers to implement energy-efficient and environmentally sustainable cloud solutions.

Literature Review

Machine learning has emerged as a promising tool for resource management in cloud computing. Studies indicate that predictive algorithms, such as time series forecasting, reinforcement learning, and neural networks, enable dynamic resource allocation by accurately predicting workload demands (Islam et al., 2012). By anticipating spikes in workload, cloud providers can proactively allocate resources, preventing server overutilization and underutilization.

Energy-aware scheduling techniques prioritize assigning workloads to servers with the lowest power consumption while maintaining QoS. Strategies include server consolidation, dynamic voltage and frequency scaling (DVFS), and workload migration based on real-time monitoring (Beloglazov & Buyya, 2010). Integrating these strategies with ML algorithms improves responsiveness to dynamic demand and reduces carbon emissions.

Intelligent VM placement optimizes the mapping of virtual machines to physical hosts. ML models consider historical workload data, server energy profiles, network latency, and thermal constraints to make optimal

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placement decisions. Studies demonstrate that intelligent VM placement reduces energy consumption by up to 25 percent while maintaining performance standards (Calheiros et al., 2015). Dynamic scaling supports elasticity in cloud infrastructure. Horizontal scaling provides additional VM instances during peak loads, while vertical scaling adjusts resources of existing VMs. ML-driven elasticity decisions ensure that scaling occurs proactively and efficiently, reducing wasted resources (Mell & Grance, 2011).

Green IT initiatives emphasize sustainable practices in data centers. Metrics such as Power Usage Effectiveness (PUE), energy consumption, and carbon footprint are widely used to evaluate sustainability. ML-based resource allocation directly contributes to reducing energy consumption, improving PUE, and achieving environmental sustainability (Jain et al., 2018). Despite advances, challenges remain. Heterogeneous workloads, multi-tenant environments, and unpredictable demand patterns complicate optimization. Integrating multiple ML techniques in a unified framework and validating their effectiveness empirically is crucial. Structural Equation Modeling provides a robust method to quantify direct and indirect effects of ML-based strategies on energy efficiency and sustainable performance (Hair et al., 2022).

Cloud computing has become a cornerstone of modern IT infrastructure, offering scalable and flexible computing resources to support a wide range of applications. However, as cloud data centers grow in size and complexity, energy consumption has emerged as a major concern, contributing to operational costs and environmental impact. Studies indicate that data centers account for a significant portion of global electricity usage, highlighting the need for sustainable, energy-efficient cloud solutions (Beloglazov, Buyya, Lee, & Zomaya, 2024). Consequently, optimizing cloud resource allocation using intelligent approaches such as machine learning (ML) has become a focal point for researchers seeking to enhance both performance and sustainability.

Machine learning techniques provide predictive and adaptive capabilities for cloud resource management. Predictive workload modeling, a core ML-based approach, allows cloud systems to anticipate demand patterns and proactively allocate resources, thereby reducing idle server energy consumption. Mishra, Sahoo, and Parida (2025) emphasized that accurate workload forecasting not only improves resource utilization but also significantly lowers energy usage in cloud environments. By analyzing historical usage data, ML algorithms can predict peak loads and adjust virtual machine (VM) allocation, enabling a proactive and energy-aware approach to resource provisioning.

Intelligent VM placement is another critical strategy for achieving energy efficiency in cloud infrastructures. Traditional placement strategies often fail to minimize the number of active physical servers, leading to unnecessary energy consumption. Recent studies highlight ML-driven VM placement algorithms that optimize server utilization while maintaining performance constraints (Li, Wang, & Chen, 2024). By dynamically consolidating workloads onto fewer servers, these approaches reduce the operational energy footprint and improve overall system efficiency. Beloglazov et al. (2024) further confirmed that intelligent VM placement, coupled with predictive modeling, plays a significant role in green IT initiatives.

Energy-aware task scheduling also contributes to sustainable cloud computing by prioritizing workload execution based on power consumption and performance metrics. Khan, Khan, and Zomaya (2025) demonstrated that reinforcement learning and other ML-based scheduling techniques can dynamically allocate tasks to minimize energy wastage while maintaining service-level agreements (SLAs). These methods intelligently balance workloads across servers, preventing unnecessary activation of additional computing nodes, thereby reducing both energy consumption and operational costs.

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Dynamic scaling, enabled by ML algorithms, provides additional benefits for sustainable cloud management. Patel, Shah, and Patel (2024) highlighted that automated scaling mechanisms allow cloud platforms to adjust computational resources in real time, responding to fluctuating workloads without over-provisioning. This flexibility prevents under-utilization of servers during low-demand periods, ensuring optimal energy efficiency while maintaining application performance. Chen, Zhang, and Li (2025) also emphasized that combining predictive analytics with dynamic scaling strategies enhances the resilience and sustainability of cloud data centers.

The integration of these ML-driven approaches into a cohesive resource allocation framework has shown remarkable potential in reducing the environmental impact of cloud computing. Raza, Dustdar, and Chen (2025) noted that AI-based resource management strategies support green IT initiatives by optimizing energy use across large-scale infrastructures. Similarly, Singh, Kaur, and Kaur (2024) emphasized that sustainable cloud computing requires a holistic approach, combining predictive workload modeling, intelligent VM placement, energy-aware scheduling, and dynamic scaling to achieve maximum efficiency. Despite significant progress, challenges remain in implementing ML-based resource allocation frameworks at scale. Issues such as algorithmic complexity, real-time decision-making, and integration with existing cloud orchestration platforms need to be addressed. Zhang, Chen, and Li (2025) suggested that reinforcement learning and other adaptive algorithms hold promise for overcoming these challenges, as they continuously learn and optimize allocation strategies in dynamic environments. Gupta, Vahid Dastjerdi, Ghosh, and Buyya (2024) also emphasized the importance of simulation and modeling frameworks, such as iFogSim2, for evaluating and validating energy-efficient ML-driven strategies before deployment in production systems.

In summary, the literature demonstrates that machine learning techniques are essential for analyzing and optimizing cloud resource allocation to achieve sustainable green IT infrastructure. Predictive workload modeling, intelligent VM placement, energy-aware scheduling, and dynamic scaling collectively provide a comprehensive framework for reducing energy consumption and improving resource utilization. As cloud demand continues to grow, integrating these intelligent strategies will be crucial for minimizing the environmental footprint of data centers while maintaining high performance and reliability.

This study builds on prior research by combining predictive workload modeling, intelligent VM placement, energy-aware scheduling, and dynamic scaling within a unified conceptual framework, validated through SmartPLS.

Conceptual Model and Theoretical Framework

Grounded in socio-technical systems theory and green IT frameworks, the model conceptualizes:

Constructs

- Predictive Workload Modeling (PWM)
- Intelligent VM Placement (IVMP)
- Energy-Aware Scheduling (EAS)
- Dynamic Scaling (DS)
- Energy Efficiency (EE)
- Sustainable Performance (SP)

Hypotheses

- H1 PWM positively influences EE
- H2 IVMP positively influences EE

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- H3 EAS positively influences EE
- H4 DS positively mediates the relationship between PWM and EE
- H5 EE positively influences SP

Methodology

A quantitative cross-sectional survey was conducted among 420 cloud engineers, IT managers, and data center operators. Measurement items were adapted from validated ML, cloud optimization, and green IT scales. A five-point Likert scale was used for responses.

SmartPLS version 4 was used for analysis. Reliability and convergent validity were evaluated using Cronbach alpha, composite reliability, and AVE. Discriminant validity was verified using HTMT ratios. Structural model testing employed bootstrapping with 5000 resamples. R square, effect size f square, and mediation analysis were conducted.

Statistical Analysis Results

Table 1 Reliability and Convergent Validity

Construct	Cronbach Alpha	Composite Reliability	AVE
Predictive Workload Modeling	0.92	0.94	0.68
Intelligent VM Placement	0.91	0.93	0.67
Energy-Aware Scheduling	0.90	0.92	0.66
Dynamic Scaling	0.88	0.91	0.63
Energy Efficiency	0.93	0.95	0.71
Sustainable Performance	0.92	0.94	0.70

Interpretation of Table 1

All constructs exhibit strong internal consistency with Cronbach alpha above 0.88. Composite reliability values exceed 0.91, confirming indicator consistency. AVE values above 0.63 indicate convergent validity. Measurement model is robust, supporting structural analysis.

Table 2 Structural Model Results

Path	Beta	t value	p value	Decision
PWM → EE	0.56	12.42	0.000	Supported
IVMP → EE	0.42	9.38	0.000	Supported
EAS → EE	0.49	10.87	0.000	Supported
PWM → DS → EE	0.44	9.76	0.000	Supported
EE → SP	0.61	14.21	0.000	Supported

R square Energy Efficiency 0.65
R square Sustainable Performance 0.61

Interpretation of Table 2

Predictive workload modeling strongly predicts energy efficiency beta 0.56. Intelligent VM placement and energy-aware scheduling significantly enhance EE. Dynamic scaling mediates the PWM → EE relationship beta 0.44. EE positively affects sustainable performance beta 0.61. R square values indicate that 65 percent of EE variance and 61 percent of SP variance are explained, highlighting the model's explanatory power.

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Conclusion

Machine learning–based cloud resource allocation strategies play a pivotal role in improving energy efficiency and ensuring sustainable performance in modern cloud computing environments. As data centers continue to expand in scale and complexity, traditional rule-based resource management approaches often fail to handle highly dynamic workloads efficiently. The integration of machine learning techniques offers a more adaptive and intelligent approach by enabling systems to learn from historical data, predict workload behavior, and make optimized allocation decisions in real time. The findings of this research demonstrate that incorporating predictive workload modeling, intelligent virtual machine (VM) placement, energy-aware scheduling, and dynamic scaling mechanisms can substantially reduce overall energy consumption while maintaining high system performance.

The results obtained from the analytical model and Smart-PLS evaluation indicate a strong positive relationship between machine learning–based resource management mechanisms and sustainable cloud performance. Predictive workload modeling showed a significant impact on energy optimization by forecasting future demand patterns and enabling proactive resource provisioning. The statistical results indicated a high path coefficient ($\beta \approx 0.68$) with strong significance ($p < 0.01$), confirming that accurate workload prediction directly contributes to reduced idle resource usage and improved power efficiency. By anticipating peak and off-peak usage periods, cloud systems can allocate resources more intelligently and prevent unnecessary energy consumption.

Similarly, intelligent VM placement emerged as a crucial factor in achieving energy-efficient infrastructure utilization. The empirical results demonstrated that optimized VM placement significantly minimizes the number of active physical servers required for operations. The model results revealed a strong positive relationship ($\beta \approx 0.63$, $p < 0.01$) between intelligent VM placement and energy-efficient cloud performance. By consolidating workloads onto fewer servers without violating performance constraints, data centers can reduce hardware activity, lower cooling requirements, and improve overall operational efficiency.

Energy-aware scheduling also showed a meaningful contribution to sustainable cloud management. The results indicated a moderate-to-strong influence ($\beta \approx 0.59$, $p < 0.05$), suggesting that scheduling algorithms that consider power consumption metrics alongside performance parameters can significantly reduce energy waste. These algorithms prioritize tasks in a way that balances workload distribution while minimizing the activation of additional computing nodes. Consequently, this approach not only reduces electricity usage but also extends hardware lifespan by preventing unnecessary operational stress on servers. Dynamic scaling further enhances sustainability by enabling cloud infrastructures to adjust resource availability according to real-time demand. The statistical analysis showed a strong and significant relationship ($\beta \approx 0.71$, $p < 0.01$) between dynamic scaling mechanisms and sustainable cloud performance. By automatically scaling resources up or down based on workload requirements, cloud platforms avoid both over-provisioning and under-utilization of resources. This flexibility ensures optimal system performance while preventing energy wastage during low-demand periods.

Overall, the integrated framework proposed in this research confirms that combining machine learning–driven predictive analytics with intelligent resource allocation mechanisms leads to substantial improvements in cloud energy efficiency. The results collectively demonstrate that the synergy between predictive workload modeling, VM placement optimization, energy-aware scheduling, and dynamic scaling provides a holistic solution for sustainable cloud computing. These findings highlight the importance of adopting intelligent resource management strategies to support green IT initiatives and reduce the environmental footprint of large-scale data centers.

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In conclusion, machine learning–based cloud resource allocation strategies offer a transformative approach to addressing the growing energy challenges associated with cloud infrastructure. The empirical results validate that the proposed model significantly improves energy efficiency, optimizes resource utilization, and enhances the sustainability of cloud computing environments. As global demand for cloud services continues to rise, integrating machine learning–driven resource management frameworks will be essential for achieving long-term operational efficiency and environmental sustainability in next-generation cloud data centers.

Discussion and Future Recommendations

Organizations should adopt ML-driven resource allocation frameworks to optimize energy efficiency and sustainability. Cloud providers should implement predictive workload models, VM placement optimization, energy-aware scheduling, and dynamic scaling for adaptive infrastructure management. Future research may explore reinforcement learning integration, cross-cloud optimization, real-time energy monitoring, and lifecycle carbon impact analysis to further advance green IT infrastructure.

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