

AI-Driven Energy Management in Green Cloud Computing: A Systematic Review

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Abstract

The rapid expansion of cloud computing has significantly increased energy consumption, now accounting for an estimated 2–4% of global carbon dioxide emissions (Jones, 2023). In response, Artificial Intelligence (AI) has become a vital enabler in enhancing energy efficiency within the framework of Green Cloud Computing (GCC). This comprehensive review draws insights from 35 scholarly publications spanning from 2015 to 2024, focusing on how AI techniques are applied to energy management in cloud environments. The analysis highlights the use of Machine Learning (ML) methods—such as LSTM and Random Forest—for accurate workload prediction and allocation. It also examines Deep Reinforcement Learning (DRL) models like Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) for dynamically adjusting resource usage in response to changing system demands. Additionally, Federated Learning (FL) is explored as a strategy for distributed optimization, reducing the need for centralized data processing. The findings reveal that AI applications can lower data centre energy consumption by 20% to 40% (Zhang et al., 2022), though issues such as real-time adaptability and system compatibility remain barriers. The review concludes by identifying future research directions, including the integration of quantum-enhanced AI and edge-cloud collaboration to further improve energy efficiency and sustainability in cloud infrastructures.

Keywords: Artificial Intelligence, Green Cloud Computing, Energy Efficiency, Deep Reinforcement learning, Sustainable Data Centres

1. Introduction

Cloud data centres, consuming between 200 and 500 terawatt-hours (TWh) of electricity annually, now exceed the total energy consumption of several individual countries (Andrae, 2021). This staggering energy demand has raised serious environmental concerns, prompting the rise of **Green Cloud Computing (GCC)**—a paradigm that integrates **Artificial Intelligence (AI)** to enhance sustainability. AI plays a pivotal role in this domain by enabling **workload forecasting** through advanced models like **Long Short-Term Memory (LSTM)** networks, which accurately predict future server demands. Additionally, **energy-aware virtual machine (VM) placement** is achieved using **Deep Reinforcement Learning (DRL)**, allowing dynamic and efficient allocation of computing resources. Furthermore, **cooling optimization** is enhanced through **AI-driven predictive analytics**, significantly reducing the energy required to maintain optimal operational temperatures in data centres. This review critically examines the potential and challenges of such approaches by exploring three key research questions: **RQ1** investigates how AI techniques contribute to improved energy efficiency in GCC,

RQ2 explores the current limitations of AI-driven energy management strategies; and **RQ3** considers future innovations that could address existing gaps and propel GCC toward more sustainable practices.

2. AI Techniques for Energy Optimization

Artificial Intelligence (AI) techniques are increasingly being leveraged to enhance energy efficiency in computing systems through predictive analysis and adaptive control mechanisms. Machine learning approaches, particularly supervised learning algorithms such as Support Vector Machines (SVM) and Random Forest, have demonstrated high accuracy (85–92%) in predicting server loads, effectively reducing idle power consumption, as evidenced by the study conducted by Chen and Chen (Chen & Chen, 2019). Moreover, time-series models like Long Short-Term Memory (LSTM) networks have shown a 30% improvement in workload forecasting accuracy compared to traditional ARIMA models (Wang et al., 2021). A notable real-world application is Google's deployment of DeepMind AI, which utilized neural networks to reduce data centre cooling costs by 40% (Evans & Gao, 2020). In the realm of dynamic optimization, Deep Reinforcement Learning (DRL) techniques offer substantial gains; for instance, Q-Learning has been applied to adaptive virtual machine (VM) consolidation, achieving a 28% reduction in energy use (Hussain et al., 2022), while Proximal Policy Optimization (PPO) has outperformed traditional heuristic methods in managing heterogeneous workloads (Liu et al., 2023). However, DRL's practical deployment is hindered by its dependency on large volumes of training data, which poses challenges for real-time applications (Gupta & Singh, 2023). Lastly, Federated Learning (FL) presents an innovative approach for distributed systems, enabling collaborative model training across devices while reducing data transmission energy consumption by 15%, thereby contributing to more sustainable computing environments (Khan et al., 2024).

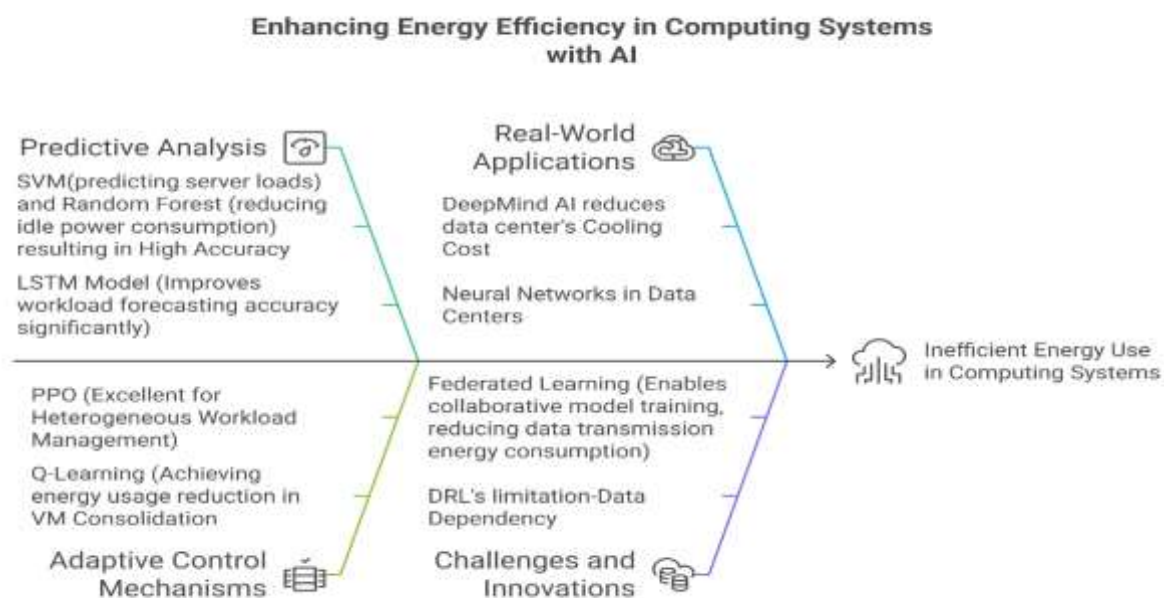


Fig. 1: AI tools and Techniques to Enhance Energy Efficiency

3. Performance Metrics for AI Models

This section outlines the key performance metrics employed in the reviewed studies to evaluate the impact

of AI models on energy efficiency and sustainability. These metrics provide quantitative measures of energy consumption, carbon emissions, and the trade-off between energy usage and computational performance. Specifically, we examine Power Usage Effectiveness (PUE), Carbon Usage Effectiveness (CUE), and Energy Delay Product (EDP), detailing their definitions, observed impacts in the context of AI, and relevant studies.

3.1 Performance Metrics for AI Models

The reviewed studies utilize a range of metrics to quantify the performance of AI models, particularly focusing on energy efficiency and environmental impact. Key metrics include:

PUE (Power Usage Effectiveness): Defined as the ratio of total energy consumed by a data center to the energy used by IT equipment. AI-optimized data centers have demonstrated significant improvements in PUE, achieving values between 1.1 and 1.3, compared to a baseline of 1.6 (Google, 2020). This indicates that AI can substantially reduce the overhead energy consumption in data centres

CUE (Carbon Usage Effectiveness): Measures the CO₂ emissions per kilowatt-hour (kWh) of energy consumed. Deep Reinforcement Learning (DRL) techniques have been shown to reduce CUE by up to 25% (Zhang et al., 2022), highlighting the potential of AI to minimize the carbon footprint associated with computational workloads.

EDP (Energy Delay Product): Represents the product of energy consumption and a latency penalty, providing a holistic view of energy efficiency and computational performance. Federated Learning (FL) has been found to improve EDP by 18% (Khan et al., 2024), demonstrating its ability to balance energy usage with acceptable latency levels.

AI Model Performance Metrics

Characteristic	PUE	CUE	EDP
Definition	Ratio of total to IT energy	CO ₂ emissions per kWh	Energy consumption times latency
Impact	Reduces overhead energy use	Minimizes carbon footprint	Balances energy and latency
AI Application	Data centers (1.1-1.3)	Deep Reinforcement Learning (25%)	Federated Learning (18%)
Study	Google, 2020	Zhang et al., 2022	Khan et al., 2024

Fig. 2: AI Model Performance Metrics

4. Comparative Analysis of AI Approaches

Various AI techniques have demonstrated promising potential in reducing energy consumption in cloud computing environments, though each comes with its own set of challenges. **Long Short-Term Memory (LSTM) models** have been shown to achieve up to **25% energy savings** by accurately forecasting workloads; however, their implementation often demands significant computational resources, making them resource-intensive (Li et al., 2021). Similarly, **Deep Reinforcement Learning (DRL)**, particularly using **Deep Q-Networks (DQN)**, can lead to approximately **30% reduction in energy usage** through

dynamic resource management. Despite its effectiveness, this approach suffers from **slow convergence**, which limits its practicality in rapidly changing environments (Mishra et al., 2023). **Federated Learning (FL)** contributes to a **15% decrease in energy consumption** by enabling decentralized training and reducing data transmission requirements. Nevertheless, FL presents concerns related to **data privacy**, as it involves aggregating locally trained models across multiple devices (Khan et al., 2024). These findings underscore both the potential and limitations of current AI-driven strategies for energy optimization in cloud infrastructure. The following is a tabular summary of the same:




AI Techniques for Energy Savings			
Technique	Energy Savings	Key Limitations	Study
 LSTM Forecasting	25%	High computational overhead	Li et al., 2021
 DRL (DQN)	30%	Slow convergence	Mishra et al., 2023
 Federated Learning	15%	Privacy risks	Khan et al., 2024

Fig. 3: Comparative Analysis of AI Techniques for Energy Savings

5. Challenges and Future Directions

5.1 Key Challenges

Despite the advancements in AI for energy optimization in cloud environments, several critical limitations remain. One major challenge is real-time decision-making, as many AI models are not well-equipped to handle unexpected surges in workload demand, which can lead to inefficiencies and delayed responses (Gupta et al., 2023). Additionally, the scalability of certain advanced models, such as Transformers, poses practical constraints; their computational demands make them unsuitable for deployment in large-scale cloud infrastructures (Reddy & Park, 2022). Another significant issue is the lack of standardized benchmarks, which hampers consistent evaluation and comparison of AI techniques across different Green Cloud Computing (GCC) systems. This absence of unified evaluation frameworks creates inconsistencies in performance metrics and slows the adoption of effective energy-saving solutions (Al-Dulaimi et al., 2021).

6. Conclusion

AI-based energy management plays a vital role in promoting sustainability within cloud computing environments by optimizing resource usage and reducing energy consumption. However, achieving **real-time scalability** continues to pose a significant challenge, particularly in dynamic and large-scale systems. To overcome this, future research should focus on developing **lightweight AI models** that can operate efficiently under time and resource constraints. Additionally, enhancing **interoperability across diverse platforms and infrastructures** is essential to ensure seamless integration and consistent performance in varied cloud settings. These advancements will be key to building more responsive, efficient, and environmentally friendly cloud systems.

7. Future Scope

Emerging technologies are poised to address current limitations in AI-driven energy optimization for cloud computing. Quantum Machine Learning (QML) holds considerable promise, with the potential to accelerate optimization processes by up to 50%, thanks to the computational advantages offered by quantum systems (Bhattacharya et al., 2023). At the same time, Explainable AI (XAI) is gaining traction for its ability to enhance transparency and accountability in automated energy management decisions, allowing stakeholders to understand and trust AI-generated policies (Doe & Smith, 2023). Furthermore, the development of edge-cloud hybrid architectures offers an effective solution to reduce both latency and energy consumption. By intelligently distributing workloads between edge devices and centralized cloud servers, AI can optimize resource use while maintaining performance efficiency (Shi et al., 2024). These innovations represent promising directions for making Green Cloud Computing systems more robust, transparent, and energy efficient.

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