International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 12, No. 3, 2025, pp. 413-423.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Optimization of Energy Consumption in Green Data Centers Using Multi-Agent Reinforcement Learning

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Abstract

Data centers are now an important infrastructure to the digital economy; yet, they also consume the most electricity in the information technology industry. The swift development of cloud computing, artificial intelligence, and the massive processing of data has greatly raised the level of energy consumption, resulting in a decrease in operational expenditures and environmental issues. The goal of green data centers is to improve such cases by designing systems that are resource-efficient and by using smart resources in managing the system. Nevertheless, it is a complex issue to optimize energy consumption since the workload changes dynamically, there exist thermal constraints, and subsystems of computing and cooling are interdependent. In this paper, a Multi-Agent Reinforcement Learning (MARL)-based model will be suggested to optimize the green data center energy consumption. The suggested model implements several smart agents that handle the workload scheduling, server control, and cooling. These agents engage with the environment and learn optimum policies through the reinforcement learning methodologies and implement adaptive and real-time decisions in different operational environments. The workload datasets are realistic, and they are used to determine the effectiveness of the proposed approach in a simulated data center environment. The findings suggest that the MARL framework can attain a maximum of 29% of energy savings and 83% of better resource utilization, compared to the traditional rule-based, DVFS-based, and single-agent reinforcement learning algorithms. The model also has a low rate of SLA violation, which guarantees a good service performance. In general, the results have supported that multi-agent learning can offer an efficient, scalable, and sustainable method of energy optimization in a modern data center, and that it has a future role in cloud and edge computing systems.

Keywords: Multi-Agent Reinforcement Learning, Green Data Centers, Energy Optimization, Resource Allocation, Cooling System Management, Sustainable Computing.

DOI: 10.71086/IAJSE/V12I3/IAJSE1277
Received: 19 July 2025/Revised: 26 August 2025/Accepted: 12 September 2025/Published: 30 September 2025

Introduction

The rapid expansion of digital technologies, including cloud computing, big data analytics, artificial intelligence, and Internet of Things (IoT) applications, has put a drastic strain on the data processing and storage infrastructure on a large scale. The backbone of such digital services is the data centers, which offer the computing power, networking, and storage of data (Huang et al., 2021). Nevertheless, the data center functioning consumes a significant amount of energy, and thus, it is one of the most energy-consuming elements of the contemporary information technology environment (Escobedo et al., 2024). Recently estimates indicate that data centers throughout the globe utilize a significant amount of overall power consumed worldwide. With growing numbers of digital services available, this consumption will continue to grow.

The two main sources of energy used in data centers are IT equipment operation and cooling systems. Servers, storage devices, and networking devices use a lot of electricity to sustain the computational performance. Meanwhile, cooling devices like air conditioning systems, liquid coolers, etc., need to be brought in to keep the temperatures at harmless levels to allow these devices to operate safely. Managing such systems ineffectively may lead to reduced efficiency in the use of energy, high operations, and carbon emissions.

In order to overcome these issues, green data centers have been developed as a sustainable solution that would reduce the impact on the environment by ensuring high performance (Yi et al., 2020). Green data centers have used energy-efficient hardware, virtualization, renewable energy, and superior resource management techniques (Sivakumar et al., 2024). Regardless of these developments, the optimization of energy consumption is complicated by such factors as dynamic workloads, changes in the environmental conditions, and the interdependence of the behavior of various components of the system (Uddin & Rahman, 2012).

The latest developments in the field of artificial intelligence and machine learning have created new possibilities for smart energy management in data centers (Berral et al., 2010; Haghshenas et al., 2019). In particular, reinforcement learning (RL) has received such popularity due to its capabilities to learn optimal decision-making methods based on its interaction with dynamic environments. Nevertheless, the conventional single-agent proposals of reinforcement learning are usually not effective in working with massive systems where several elements need to be managed at the same time.

The multi-agent reinforcement learning approach has become a viable approach to overcoming limitations and performing distributed decision-making in complex environments. The MARL framework comprises several intelligent agents working together or against each other to optimize shared objectives. Data center management can include the separate management of different subsystems, e.g., workload scheduling, activating servers, and implementing cooling systems, with their activities coordinated to minimize total energy consumption.

This study suggests a multi-agent reinforcement learning (MARL) structure to maximize the energy usage in green data centers. The research problem is the possibility of many agents working together to manage both computational resources and cooling systems to enhance energy efficiency and ensure that the performance of systems is not affected. The model proposed is a combination of real-time tracking of system conditions, adaptive learning policies, and agent-agent interaction to obtain the best operational strategies.

The main contribution of this paper includes,

- Introduces a new Multi-Agent Reinforcement Learning (MARL) framework for energy use optimization of green data centers by using distributed and coordinated decisions.
- Creates a response mechanism that is entirely integrated in controlling the usage of servers, the distribution of the workload, as well as cooling systems to provide better energy consumption.
- Formulates an active reward-based optimization model that trades off between energy minimization and Service Level Agreement (SLA) performance limits.
- Demonstrates through simulation experimentation, large increases in energy efficiency, resource use, and system stability over traditional and single-agent designs.

This paper will be structured in the following way: Section 2 will provide the literature survey, and the research gap will be identified afterward. Section 3 outlines the proposed MARL-based strategy, architecture, algorithm, and mathematical model. Section 4 provides the description of the experimental setup, the dataset, and its results and performance analysis. Lastly, Section 5 summarizes the paper by highlighting findings and research directions.

Literature Review

Energy optimization in data centers has gained more attention in recent studies in the assumption of reinforcement learning (RL) and multi-agent systems, which deal with the dynamic workload and energy management issues.

The above study proposed a multi-agent reinforcement learning approach to scheduling renewable energy in distributed clouds and demonstrated improvements in both scalability and operational cost savings (Jayanetti et al., 2024; Gopalakrishnan et al., 2024). Likewise, a second study used MARL to devise a global optimization technique to coordinate supply and demand for energy in prosumer data centers (Yang et al., 2024). These investigations have highlighted the growing importance of distributed intelligence for managing data centers with consideration to energy consumption (Attia et al., 2024; Sanayha & Vateekul, 2022).

The previous research examined cooperative MARL methods in order to enhance energy efficiency and the use of renewable energy, demonstrating that collaborative agents are superior to centralized methods in large-scale settings (Chi et al., 2021; Wang et al., 2021). A different paper proposed actor-critic-based RL to implement adaptive resource allocation, which has an efficient workload distribution given different demand conditions (Chen et al., 2021). Also, the recent publications showed that MARL is effective in the offloading of tasks and distributed decision-making, which supports its scalability and adaptability (Gao et al., 2023; Zhao et al., 2022).

In terms of cooling and infrastructure optimization, these studies were used to solve deep reinforcement learning on the HVAC and cooling control that had attained substantial energy consumption savings (Li et al., 2019; Wei et al., 2019). Moreover, such works were dedicated to the allocation of resources and load balancing with the help of RL and in order to enhance the performance of the system and lessen the idle resources consumption (Thein et al., 2020; Arezoo & Abolfazl, 2020).

According to the literature, although RL-based approaches greatly enhance the energy efficiency, most studies consider the optimization of single-component optimization, as in the case of scheduling, cooling, or resource allocation alone. Recent MARL methods are focused on scaling but do not typically consider control of multiple subsystems. Thus, the proposed study has an advantage over the existing literature because it suggests a single structure of MARL that can optimally manage servers, allocate the workload, and regulate the cooling process, and thus addresses the research gap identified and helps to make green data centers overall more energy-efficient.

Research Gap

Although there has been a considerable improvement in energy-efficient data center management, there are a number of outstanding gaps in the current literature. The majority of the conventional methods use the single-position or rule-of-thumb optimization algorithms that do not have the capability to adjust to changing workload dynamics and real-time environmental fluctuations. Despite the fact that reinforcement learning (RL) approaches have enhanced adaptability, most research concentrates on single-agent frameworks, which restrain scalability as well as synchronized decision-making in complicated data center settings. Moreover, most of the literature can be found to cover specific subsystems separately, e.g., workload scheduling, server consolidation, or cooling optimization, as opposed to a comprehensive solution involving the entire system. Although recent Multi-Agent Reinforcement Learning (MARL) models provide distributed intelligence, they do not often have a coordinated system to provide a balance between energy efficiency and system performance through a unified reward structure. The second critical weakness is that there is a lack of integration of real-time monitoring information, such as temperature, power consumption, and dynamic workload, in the decision-making process. Moreover, not all studies sufficiently cover the trade-off between the energy optimization and compliance with the Service Level Agreement (SLA), which is important to achieve the practical implementation.

Thus, an integrated and harmonized MARL-based structure, overcoming the need to integrate several data center subsystems, facilitating real-time adaptive decision-making, supporting optimal energy efficiency without compromising the reliability of the system, is mandatory.

Proposed Methodology

The given methodology presents a Multi- Agent Reinforcement Learning (MARL)-based algorithm to maximize the energy consumption in green data centers by coordinated and adaptive decision-making. The system operates in a continuous loop comprising monitoring, decision-making, action, and learning. The data center is first monitored using sensors and logging systems that record real-time values of parameters such as server utilization, workload, temperature, and power consumption. The parameters constitute the state space, and they are shared among a number of intelligent agents.

Three primary agents are deployed:

1. Workload Management Agent – responsible for distributing tasks efficiently across servers,
2. Server Control Agent – manages activation and deactivation of servers based on demand,
3. Cooling Control Agent – regulates cooling systems to maintain optimal temperature with minimal energy usage.

Energy optimization coordination within a data center environment can be coordinated through the use of three main classes of agents. The Workload Management Agent allocates tasks to the servers based on balancing workload and avoiding under-utilizing resources. The Server Control Agent is a dynamic agent that reduces the idle energy consumption of servers by activating and deactivating servers based on current demand. In addition, the Cooling Control Agent regulates the cooling systems to maintain the desired temperature while consuming less energy. The three agent classes produce actions based on the observations made in the data center. The actions of the three classes of agents result in state transitions, which contribute to changing the status of the overall data center environment. System performance is measured using one of the reward functions based on energy consumption and Service Level Agreement (SLA) compliance. In order to maximize the cumulative rewards, the agents iteratively change their rules through constant interaction with the environment. This feedback control learning architecture ensures adaptive optimization, which allows the system to operate with the least amount of overall energy while responding to changes in workload and the environment.

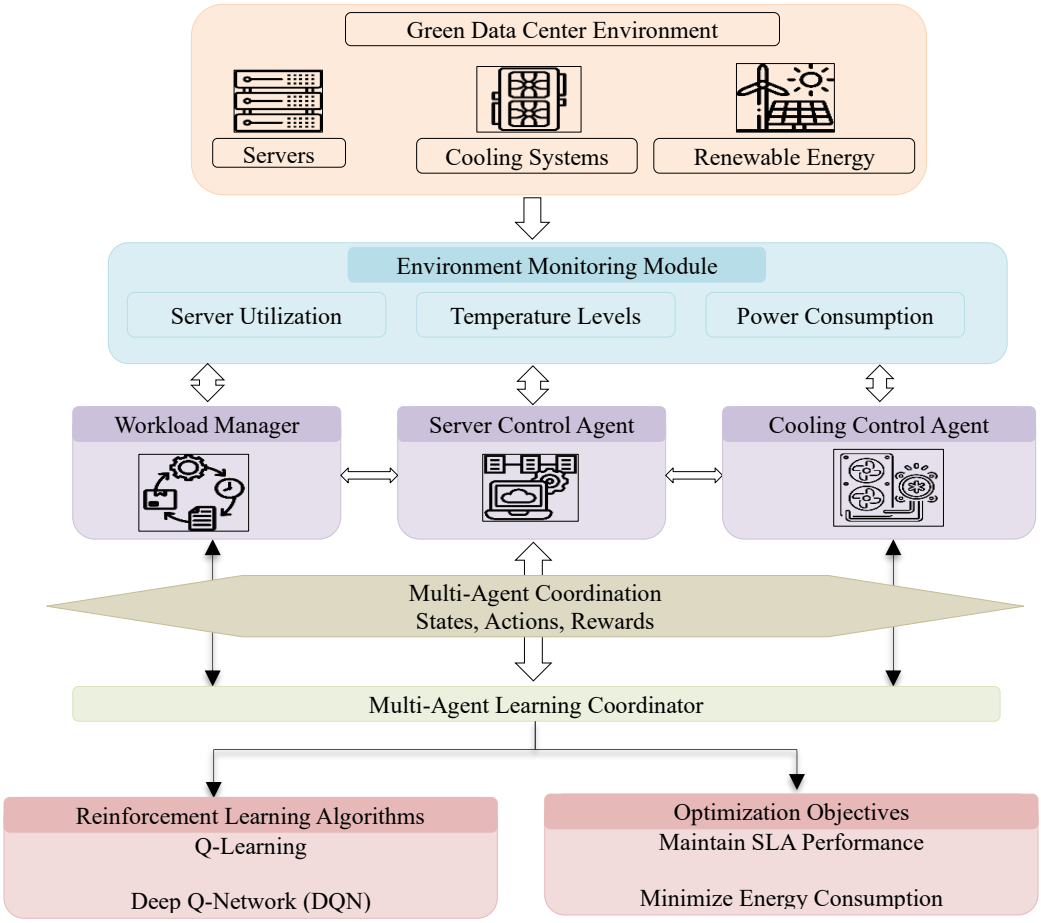


Fig. 1: Multi-Agent Reinforcement Learning Architecture for Energy Optimization in Green Data Centers

Fig. 1 comprises a green data center system comprising servers, cooling devices, and renewable energy sources. A monitoring module gathers real-time data in an environment monitor that is handled by a number of agents that manage workloads, control servers, and regulate coolers. These agents are guided by a multi-agent learning coordinator and communicate via a coordination layer, and are guided by reinforcement learning algorithms to optimize energy consumption and achieve performance.

Algorithm 1: Multi-Agent Reinforcement Learning Algorithm for Energy Optimization

Input: System state (server utilization, temperature, workload demand)

Output: Optimal actions for minimizing energy consumption

Step 1: Initialize environment and agent policies

Step 2: Observe initial state S_t

Step 3: For each time step:

- Each agent selects action A_t^iusing policy π_i
- Execute joint actions $A_t = \{A_t^1, A_t^2, A_t^3\}$
- Environment transitions to a new state S_{t+1}
- Compute reward R_t

Step 4: Update agent policies using Q-learning / Deep Q-Network:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R + \gamma \max Q(s',a') - Q(s,a)]$$

Step 5: Repeat until convergence

In Algorithm 1, various agents learn how to behave to achieve the best strategies through their interactions with the environment. All the agents keep their policy updated depending on the reward, and in such a way, they coordinate their behavior so that they can utilize less energy and at the same time ensure the performance of the system.

Mathematical Description

The given system can be modeled as the Markov Decision Process (MDP) with the extension to the multi-agent system.

State Space (S)

The state space is the index of the environmental parameters available to the agents at a given time step which are shown in equation 1. It records the present status of the operational state of the data center such as the consumption of resources, thermal status, energy usage and incoming workload. Such states allow agents to make informed decisions to maximize the energy efficiency without compromising the performance of the system.

$$S = \{U_s, T, P, W\} \quad (1)$$

Where, U_s= Server utilization, T= Temperature levels, P= Power consumption and W= Workload demand.

Action Space (A)

Action space, in this case, is the group of the decisions made by the various agents to regulate the workload allocation, server activity and cooling processes within the data center are represented in equation 2.

$$A = \{A_w, A_s, A_c\} \quad (2)$$

Where, A_w= Workload allocation decisions, A_s= Server on/off decisions, and A_c= Cooling adjustments

Energy Consumption Model

The overall energy consumption is the amount of energy consumed by the servers and cooling systems are shown in equation 3, 4 and 5. Server energy is a time dependent characteristic on the power consumed and cooling energy is a current and threshold temperature characteristic.

$$E_{total} = E_{server} + E_{cooling} \quad (3)$$

$$E_{server} = \sum_{i=1}^{n} P_i \cdot t_i \quad (4)$$

$$E_{cooling} = f(T_{current}, T_{threshold}) \quad (5)$$

Reward Function

The reward function is designed to minimize energy consumption while penalizing SLA violations are illustrated in equation 6:

$$R = -(\alpha E_{total} + \beta SLA_{violation}) \quad (6)$$

Where, α= Weight for energy consumption and β= Weight for SLA penalty

Multi-Agent Coordination

Each agent optimizes a local policy while contributing to a global reward, ensuring coordinated behavior are shown in equation 7:

$$R_{global} = \sum_{i=1}^{n} R_i \quad (7)$$

Results and Discussion

Software Details

Multi-agent reinforcement learning (MARL) model was trained on the basis of Python 3.10 and enhanced by the machine learning and simulation libraries. To create Deep Q-Network (DQN)-based agents, the environment of Deep Learning based on TensorFlow and Keras was used, which allows the agents to optimize their policies and learn efficiently. The dynamic behavior of the data center was simulated by developing a custom environment based on OpenAI Gym. NumPy and Pandas were used in preprocessing the data and in the numerical calculations, and Matplotlib was used to plot the measure of performance and comparative analysis. CloudSim Plus was also added to model and simulate real infrastructure and operations of a data center. The experiments were carried out on a system that had an Intel i7 processor, 16GB of RAM, and an NVIDIA CUDA-enabled graphic card that guaranteed the system was effective in training and converting the reinforcement learning agents faster.

Dataset Details

The experimental assessment uses realistic workload traces which are acquired in publicly available datasets, namely Google Cluster Dataset and the Alibaba Cluster Trace Dataset. All these data sets have around 1.3 million events of task, which include a full representation of scale-wide data center operations. The simulated environment uses a model of 200 servers that represent dynamic and various workload conditions. The important characteristics that have been obtained through the datasets are CPU usage, memory usage, incoming rate of tasks, execution time of tasks, and the patterns of resource requirement. These properties allow the workload variability and the behavior of the system to be modeled accurately. The fact that such massive and heterogeneous datasets are used guarantees that the suggested MARL framework can be tested in the real setting which makes it very convenient to test the effectiveness of adaptive energy optimization strategies in the current environment of data centers.

Parameter Initialization

The following parameters were initialized for training the MARL model:

Table 1: Parameter Initialization for MARL-Based Energy Optimization Model

Parameter	Value
Learning Rate (α)	0.01
Discount Factor (γ)	0.95
Exploration Rate (ε)	0.1
Number of Episodes	5000
Batch Size	64
Replay Memory Size	10,000
Temperature Threshold	20°C – 27°C
Number of Agents	3
Reward Weights (α, β)	0.7, 0.3

These parameters were selected based on empirical tuning to ensure convergence and stable learning. Table 1 demonstrates the key parameters based on the suggested Multi-Agent Reinforcement Learning model to be adjusted and trained. It possesses learning and exploration settings, training settings, environmental constraints, and reward weighting aspects. The choice of these parameters was based on empirically determined values to be able to give stable learning, efficient convergence and optimal performance at the energy optimization under the dynamic conditions of the data centers.

Performance Metrics

The following performance metrics were considered in order to access the effectiveness of the proposed system:

Energy Consumption (EC)

$$EC = \sum_{t=1}^{T} P_t \times \Delta t \quad (8)$$

Energy Consumption is determined as a summation of power usage at each time interval, which shows the overall system efficiency, and is shown in equation 8.

Power Usage Effectiveness (PUE)

$$PUE = \frac{Total\ Facility\ Energy}{IT\ Equipment\ Energy} \quad (9)$$

PUE measures the energy efficiency of a data center by comparing total energy consumption to the energy used by IT equipment. Lower PUE values indicate better energy efficiency are represented in equation 9.

Resource Utilization (RU)

$$RU = \frac{\sum_{i=1}^{n} Active\ Server\ Usage}{Total\ Server\ capacity} \quad (10)$$

Resource Usage is applied to demonstrate the effectiveness in the use of the existing server capacity. The high use implies effective use of computational facilities and reduced power wastage are shown in equation 10.

LA Violation Rate (SVR)

$$SVR = \frac{Number\ of\ Violated\ Requests}{Total\ requests} \quad (11)$$

SLA Violation Rate shows a percentage of service requests that do not comply with the predetermined performance criteria. The lesser the values, the higher the service reliability in equation 11.

Energy Efficiency Improvement (EEI)

$$EEI = \frac{E_{baseline} - E_{proposed}}{E_{baseline}} \times 100 \quad (12)$$

Equation 12 measures the percentage change in energy consumption reduction of the proposed model over the baseline methods, showing that it is effective.

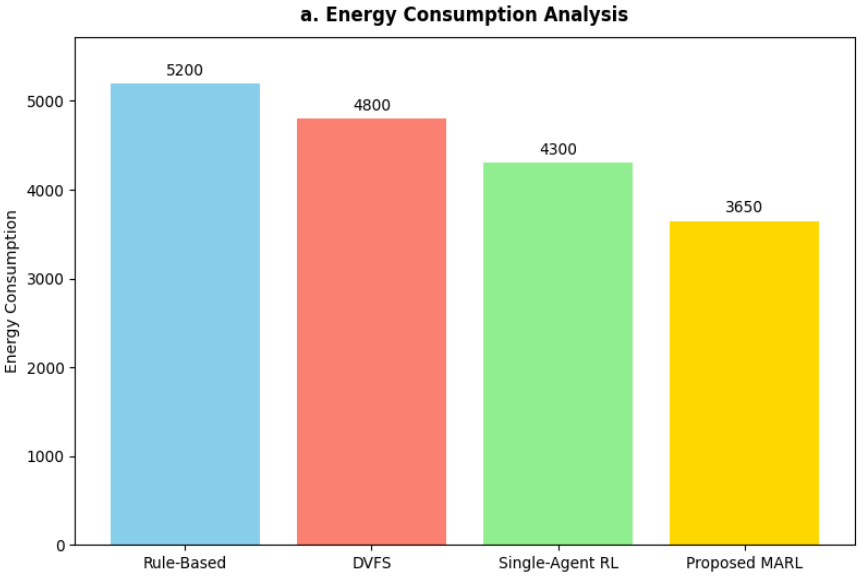
Performance Comparison

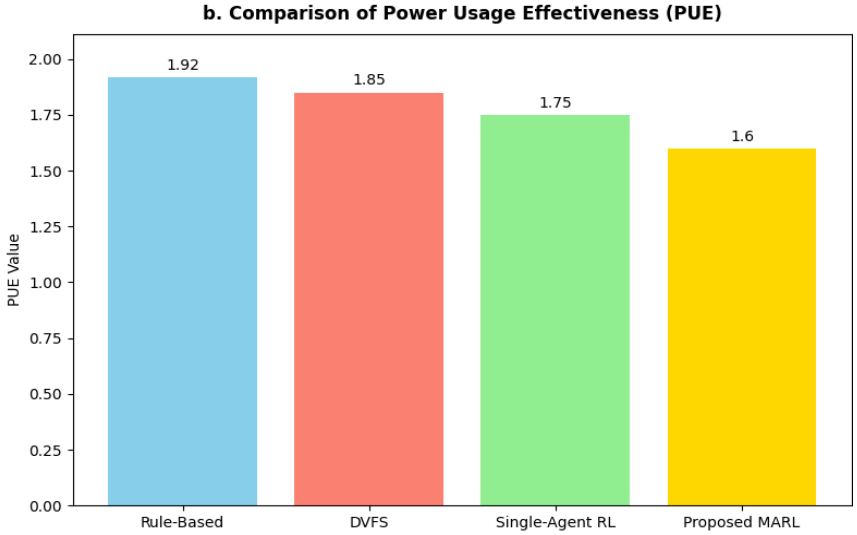
The developed Multi- Agent Reinforcement Learning (MARL) model is assessed in terms of comparing its performance with three popular baseline models. They are: Rule-Based Control based on pre-defined, static policies of resource management; Dynamic Voltage and Frequency Scaling (DVFS)-Based Optimization, which is a method of adjusting the CPU power output in order to minimize its energy consumption; and Single- Agent Reinforcement Learning, whereby decisions affecting the overall system are made by a centralized agent. The comparative analysis makes it possible to comprehensively evaluate the effectiveness of the proposed model in realizing the energy efficiency, scalability, and adaptive resource management of dynamic data center settings.

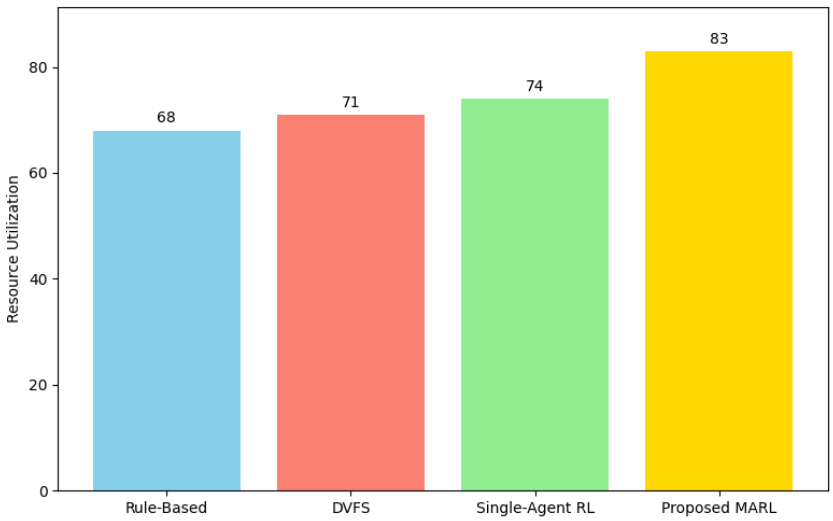
Table 2: Performance Comparison of MARL Model with Baseline Methods Across Energy and Efficiency Metrics

Method	Energy Consumption (kWh)	PUE	Resource Utilization (%)	SLA Violations (%)	EEI (%)
Rule-Based	5200	1.92	68	6.5	12
DVFS	4800	1.85	71	5.2	18
Single-Agent RL	4300	1.75	74	4.3	23
Proposed MARL	3650	1.60	83	2.1	29

Also, the MARL model's proposed advantages, including energy savings, PUE improvements, resource utilization, SLA violations, and energy efficiency gains, are compared to baseline strategies in table 2 through key performance indicators. The results prove that the MARL strategy performs the best, taking into account the enhanced system reliability and energy efficiency.


a. Energy Consumption Analysis
Energy Consumption
0
1000
2000
3000
4000
5000
5200
4800
4300
3650
Rule-Based
DVFS
Single-Agent RL
Proposed MARL


b. Comparison of Power Usage Effectiveness (PUE)
PUE Value
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
1.92
1.85
1.75
1.6
Rule-Based
DVFS
Single-Agent RL
Proposed MARL


c. Total Resource Utilization Metrics
Resource Utilization
0
20
40
60
80
68
71
74
83
Rule-Based
DVFS
Single-Agent RL
Proposed MARL

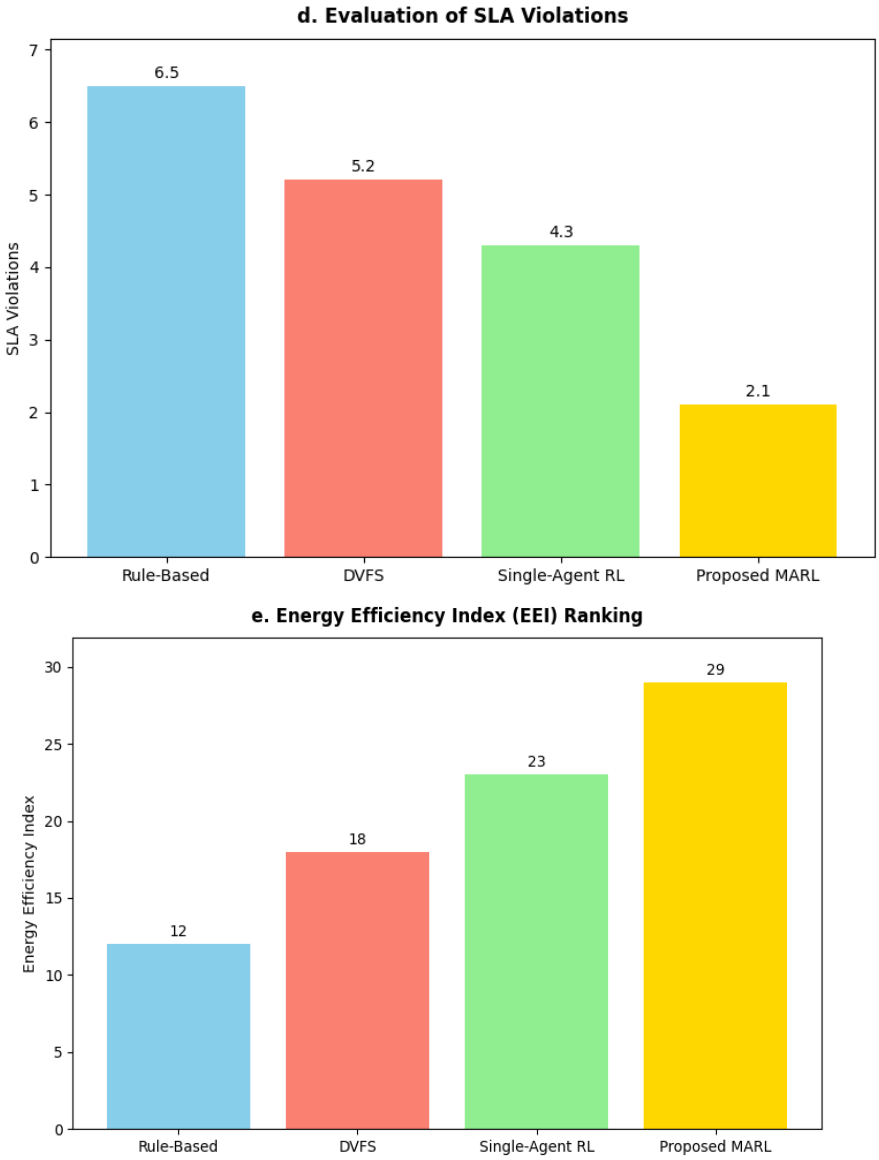


Fig. 2: Performance Evaluation of MARL Model Across Energy and Efficiency Metrics

Fig. 2 illustrates how the proposed MARL approach outperforms baseline models in key performance metrics, such as (a) energy consumption, (b) PUE, (c) resource utilization, (d) SLA violations and (e) EEI. These findings demonstrate that the MARL approach produces significantly better resource utilization and energy efficiency than existing approaches while also reducing total energy consumed and improving SLA compliance.

Discussion

Research results show the effectiveness of the proposed multi-agent reinforcement learning (MARL) architecture in optimally using energy consumptions in green data centers. Compared to traditionally used but ineffective rule-based and dynamic voltage and frequency scaling (DVFS) techniques, the MARL model provides up to a 29% reduction in energy usage due to its ability to dynamically adapt to changing workloads and environmental conditions. In addition, the increase in power usage effectiveness (PUE) provides evidence that there is greater coordination between cooling mechanisms and IT operations due in part to specialized agents monitoring multiple subsystems.

Additionally, the proposed model significantly decreased the number of service level agreement (SLA) violations, which are key in maintaining reliable service in operating data centers. This demonstrates that it is possible to achieve optimization of energy while also achieving maximization of overall system performance. Evidence of improved

resource utilization further demonstrates that the MARL approach effectively reduces the occurrence of idle server states while improving workload allocation. Agents collaborate to maintain balanced system operation through preventing resource overload/under-utilization.

Overall, the findings confirm that multi-agent reinforcement learning offers a scalable, flexible, and effective solution for sustainable data center management, making it ideal for contemporary cloud computing environments.

Conclusion

To improve energy use in green data centers, this research presented a Multi-Agent Reinforcement Learning (MARL) architecture that provided a coordinated and adaptable way to control server usage, task workloads and cooling systems. The proposed method used a distributed learning process that adapted to the changing environment and dynamically altering workloads to overcome major limitations with typical single-agent and rule-based techniques. Results of the trial demonstrated substantial increases across all evaluated performance measurements. The proposed MARL model improved on the overall efficiency of energy use (energy efficiency) by approximately 29%; reducing total power consumption from 5200 kWh (Rule based) to 3650 kWh in order to achieve a PUE of 1.60, indicating greater operating efficiencies than that of traditional methods. In addition, the violations of Service Level Agreements (SLA) were reduced to 2.1%, ensuring high reliability, and the percentage of total system resources utilized increased to 83% indicating that computational resources are being used more efficiently. The statistical analysis supports the notion that the MARL framework is capable of balancing between system performance and energy efficiency, which is critical for the sustainable operation of data centers. The findings also support the idea that using several coordinated agents improves decision-making over centralized models. Large-scale environments benefit from increased scalability and adaptability when workload management, server control, and cooling optimization are integrated into a single learning framework. Even with these encouraging findings, there are still a number of avenues for further investigation. The incorporation of renewable energy-aware optimization, in which agents dynamically modify processes based on energy availability, can be investigated in future study. The model's usefulness in distributed systems may further be improved by expanding it to edge and fog computing settings. Scalability and convergence speed may be further enhanced by utilizing sophisticated deep reinforcement learning methods like federated learning and actor-critic models. Future research should focus on real-world deployment and validation in operating data centers. All things considered, the suggested MARL framework offers a reliable and expandable way to accomplish sustainable and energy-efficient data center administration.

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