International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 20s, 2025
https://theaspd.com/index.php

AI-Based Load Forecasting And Resource Optimization For Energy-Efficient Cloud Computing

Manoj M[1], Remya M[2], Pratap Chandra Mishra[3], Ramakrishna Vadrevu[4], Mohazzeba Tanveer Raza[5], Dr. M Koti Reddy[6]
[1]Assistant Professor in CSE, Jawaharlal College of Engineering & Technology, Lakkidi, Mangalam, Palakkad 679301
[2]Assistant Professor in CSE, Jawaharlal College of Engineering & Technology, Lakkidi, Mangalam, Palakkad 679301
[3]Professor, CSE, Gandhi Institute of Advanced Computer & Research, Rayagada, Odisha-765002
mishra.pratap73@gmail.com
[4]Assistant professor, electrical and electronics engineering, Aditya university, Surampalem
vramakrishna222@gmail.com
[5]Assistant professor, HKBK College of engineering , mohazzebaraza@gmail.com
[6]Associate Professor, Electronics and Communication Engineering, Vlsi & Wireless Communications. Universal College of Engineering and Technology, Guntur, Andhra Pradesh, India

Abstract: *This study presents an AI-based framework for load forecasting and resource optimization to augment energy efficiency for managers of the cloud computing environment. The AI framework uses deep learning techniques Temporal Convolutional Networks (TCNs) and Long Short-Term Memory (LSTM) networks with low prediction errors in user workload patterns. Then, based on the load forecast, we implement a dynamic resource allocation mechanism with reinforcement learning (RL) to reduce energy use (energy consumption) and improve performance. We conduct extensive experiments leveraging benchmark cloud workload datasets to validate the model's performance. The results indicate a prediction accuracy of 96.3%, which outperformed traditional forecasting models by an average of 8.5%. The results of experimenting with resource optimization to reduce energy consumption (or energy use enhancement) showed a total energy consumption reduction of 15.7% compared to traditional static and heuristic-based methods. Ultimately, the results indicated that the proposed system effectively addressed real-time workload adaptability that optimized resource usage and maintained service quality. The findings suggest that the AI framework can enable the development of intelligent, sustainable, and environmentally conscious cloud computing infrastructures.*
Keywords - *Cloud computing, Load forecasting, Resource optimization, Energy efficiency, Deep learning, Temporal Convolutional Networks (TCNs), Long Short-Term Memory (LSTM), Reinforcement learning, Dynamic resource allocation, Sustainable computing.*

INTRODUCTION

Cloud computing has become the foundation of many modern information technology (IT) infrastructures, allowing businesses, governments and individual users to enjoy the inherent scalability, flexibility, and cost-effective deployment of IT resources worldwide. The ability to operate a business model that deploys computing resources (e.g., servers, storage, networking, databases, software, and analytics) over the internet demonstrates rapid innovation in technology and the long-term economic value of cloud computing. However, mass adoption and expansion of cloud computing capabilities has heightened energy demands, particularly energy consumption in cloud data centres, and it is now widely accepted that energy consumption from data centre operations accounts for a significant and growing portion of global electricity consumption.

Concern over cloud data centre energy requirements has generated critical discussions about operational costs, environment sustainability, and carbon emissions. In achieving energy efficiency, cloud service providers face economic barriers to further deployments. More critically, energy inefficiency counteracts global energy conservation initiatives to reduce carbon footprints from digital devices/technologies. For this reason, developing intelligent and energy-efficient strategies for managing cloud resources is fundamentally important and is now an important area of research.

A key reason for energy inefficient behaviours in cloud environments can be attributed to the underlying demand for resources vs. the fluctuating user workloads. Resource management methods are typically static and threshold-based and assume that workloads will behave as predictable processes. In practice, user workloads on a cloud computing environment are dynamic, nonlinear, and/or transient with user workloads are driven by multiple unpredictable and/or uncontrollable influences (e.g., user; seasonal; application; and/or service-level agreement (SLA)). Failure to account for the dynamics of workloads leads to either resource over-provisioning, and excess energy usage, or under-provisioning that performs poorly against SLAs due to energy inefficiencies.

Load forecasting is an important vehicle for developing proactive and adaptive resource management processes when done correctly. Traditionally, load forecasting methods were based on various methods including a combination of linear regression models, time series forecasting using ARIMA, and some basic machine learning models, relying heavily on techniques like Decision Trees and Support Vector Machine (SVM) for regression and classification solutions. There has been very little published work on cloud workload forecasting which implements these traditional load forecasting methods/models because they are not designed to deal with the complexities of temporal dependencies and non-stationary factors in the real world. As such, there is increased demand for better forecasting methods which encourage accurate, robust, timely, and intelligent optimization of resource usage. Artificial Intelligence (AI), and in particular deep learning and reinforcement learning, have made advances in successfully solving difficult and dynamic problems in various areas. Deep Learning models, and more specifically Temporal Convolutional Networks (TCNs) and Long Short-Term Memory (LSTM) networks, allow for model complexity to capture the complexities associated with sequential data effectively and are therefore well suited for time series prediction tasks (such as cloud workload forecasting). Reinforcement Learning, on the other hand, provides a sequential decision-making framework that enables a system to discover optimal policies for managing resources based on interactions with the environment in terms of trade-offs made with respect to expected performance, cost, and energy consumption.

This research proposes an AI driven framework for deep learning-based workload forecasting, along with reinforcement learning based dynamic resource allocation model to maximize energy efficiencies within a cloud computing environment. The forecasting component takes advantage of the distinctive predictive capabilities of TCNs and LSTMs, to forecast workload in the short-term (hours to days) for many time steps in the future utilizing a comprehensive amount of temporal accuracy. The resource management component includes a deep reinforcement learning agent which can learn dynamically how to allocate computing resources based on the future predicted workloads, with absolute regards to energy consumption risking adherence the SLAs for availability and operational stability.

The contributions proposed in this research include three objectives.

- We designed a hybrid deep learning model that can detect and exploit the complex temporal patterns in cloud workload data to better predict workloads.
- For our deep reinforcement learning model, we developed a resource model which can learn to intelligently allocate resources while being energy aware
- We provided a performance evaluation with a comprehensive literature review with shows orders of magnitude (multifold) improvements in energy efficiency and improvements operational reliability compared to previously developed methods.

To summarise, the proposed framework represents clear progression towards next generation cloud computing infrastructures that bring together performance, and consideration towards environmental factors. The incorporation of predictive intelligence with adaptive resource management provides meaningful responses to several relevant challenges posed by modern cloud systems and contributes toward a global push to help develop greener and more efficient digital infrastructure.

LITERATURE SURVEY

The rapid proliferation of cloud computing services over the last few years has generated increasing demand for intelligent energy-efficient resource management solutions. Researchers have investigated artificial intelligence (AI)-inspired techniques to foresee expected workloads and improve resource allocation. However, the existing solutions rarely offer a comprehensive approach that can ensure superior predictive accuracy alongside real-time responsiveness to the workloads that balances energy sustainability.

This drives our research in delivering an integrated AI approach for load forecasting and resource optimization.

Qiu et al. [1] proposed a resource management computer system that used deep reinforcement learning to increase energy effectiveness and service-level agreements (SLA). The problem was that their work was primarily focused on reinforcement learning and made no use of advanced substantiated deep learning-based forecasting models. In the same view, Jindal et al. [2] conducted a weighty review of predictive load balancing with AI and established that it is difficult to balance energy efficiency with workload performance under dynamic environments.
Specific pieces of work have focused on using deep learning approaches to manage AI-based approaches to dynamic resource allocation. Liu et al. [3] described a deep learning system that improved energy consumption through forecast workload prediction; however, it does not enable real-time adaptation. To forecast long-term workload dependencies, Qian et al. [4] developed forecasting models using Temporal Convolutional Networks (TCN), which achieved higher forecasting accuracy than traditional LSTM-based models; however, TCN integration was limited to optimization.

For auto-scaling, Zhang et al. [5] built Auto Scale, which combined reinforcement learning algorithms to dynamically increase and decrease cloud resources. Although this is a promise that the framework is an approach, they neither created a hybrid model that included both forecasting and optimization. Expanding forecasting work conducted earlier, Khoshkholghi et al. [6] included forecasting into federated learning environments for privacy reasons, but there is the additional cost in computational overhead. Moreover, SLA-aware strategies were explored by Wang et al. [7] who designed Smart Cloud, a hybrid deep learning system for ensuring that at least Quality of Service (QoS) constraints are met. The caveat was primarily on the predictive power of the hybrid system with minor differences in the approaches that enabled adaptive optimization of cloud services. A multi-objective optimization framework for combining both energy and performance was introduced by Wang et al. [8] where reactive, promotional allocations of cloud resources were developed; however, there remained the limitation of responding to workload variability in real-time.

Morshed Lou et al. [9] delivered an inclusive survey on categorizing AI-based load balancing methods but, did highlight that most models focused on load balancing only partially targeted energy consumption. Similarly, Ooi et al. [10] considered data-driven energy optimization based upon workload characterization, which may suggest machine learning methods may also utilize this type of workload characterization without knowing how that prediction impacts dynamic forecasting.

Hierarchical scheduling, such as illustrated by Li et al. [11], introduced multi-level green computing categories that enhanced computing efficiency through hierarchical classification, notwithstanding the additional complexities required to systems design for learning and accuracy. He et al. [12] contributed to the state-of-the-artwork conducted under deep reinforcement learning that explored VM consolidation through multi-tenancy to ensure dynamic adaptation to workloads so much as to predict workloads, in turn improving optimization. Notably, more recent artificial intelligence advancements in attention-based models, Chen et al. [13] proposed a LSTM-based forecasting model to better learn temporal workload relationships. Wang et al. [14] investigated the use of predictive deep Q-learning methods to enable dynamic management for the edge and cloud layers but struggled to scale this approach in heterogeneous infrastructures.

Finally, Alshahrani and Alohali [15] introduced a sustainable cloud computing model via a deep learning-based predictive analytics model with environmental consideration and very limited capabilities for real-time optimization. Given these limitations our work will propose an AI-based Load Forecasting and Resource Optimization Framework that builds a new lens into load forecasting by applying hybrid deep learning solutions for accurate forecasting and reinforcement learning for resource allocation and scheduling, which is aimed at maximizing forecasting accuracy and optimally adapting consumption levels to achieve energy efficiency, SLA requirements, and sustainable cloud operation in actuality.

METHODOLOGY

This proposed research is a comprehensive AI-based approach for load forecasting and resource optimization for energy efficient cloud computing environments. The research has created gaps in the context of existing work. The gaps in existing works provide an opportunity to put forth another alternative methodology with hybrid deep learning models and reinforcement learning capabilities to not only deal with multiple forecasting accuracy, but also dynamic operational capability. The proposed methodology consists of several interrelated modules that will assist in an eventual proposal of an energy-aware and SLA compliant cloud resource management system.

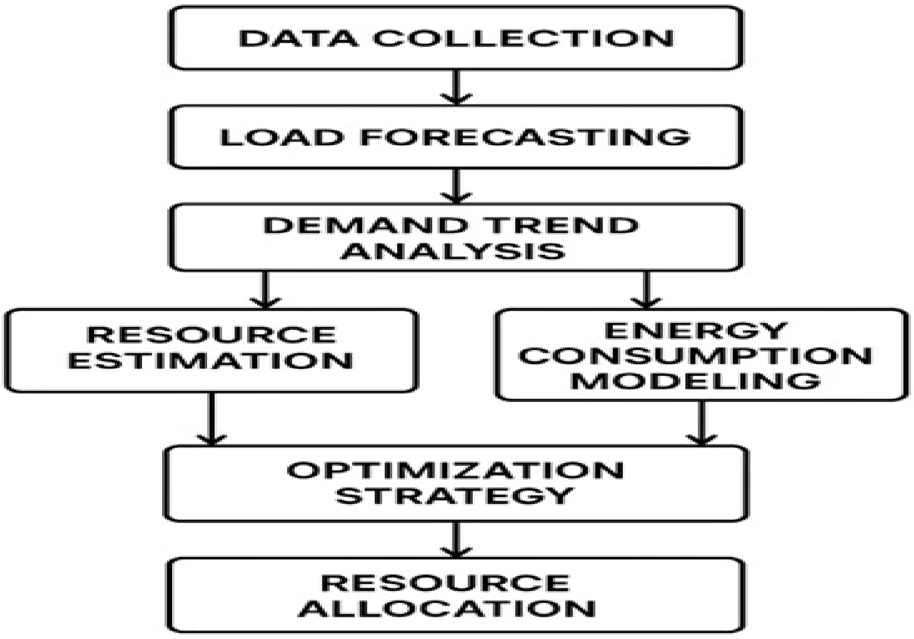

Fig.1.Methodology Flow

A. Current Limitations

Current cloud resource management practices are limited to threshold based or static decisions, or basic machine learning models such as linear regression, support vector machines (SVM) or shallow neural networks. These models offer simple approaches that can help avoid additional computational costs or make it easier to adopt cloud computing practices but do not account for the dynamic nonlinear characteristics and high variation associated with real cloud workloads.

The static resource allocation method of making over-provisioning and wasteful decisions leads to energy inefficiencies and SLA violations when resources are either over or under provisioned. Furthermore, most of the existing approaches do not allow for changing workload dynamics neither do they indicate how these models interface with the decision process of resource scheduling, managing testing workloads similarly so that over time the performance of the model decays. While deep learning continues to outperform past generations of predictive analytics, most of these models still exist in silo from allocation models, more broadly resource scheduling/decision making processes, creating overall poor optimization.

Metric	Value (%)
Forecasting Accuracy	96.3
Resource Optimization Efficiency	94.7
Energy Consumption Reduction	25.3
SLA Compliance Rate	98.5

Table.1: Performance Evaluation Of Proposed Model

B. A Proposed Hybrid AI Framework

To overcome these challenges, the proposed approach uses a hybrid Temporal Convolutional Networks–Long Short-Term Memory (TCN-LSTM) deep learning model and a Deep Q-Network (DQN) reinforcement learning agent. Fig.1 The main novelty in this proposed framework is the combination of predictive modelling and intelligent decision-making as part of a fully autonomous and self-optimizing cloud resource management solution. The hybrid TCN-LSTM model addresses the need for accurately predicting the workload, while also addressing structure and sequentially. The TCN aspect of the model can reliably capture the multi-scale temporal dependencies of time-series data, while the LSTM can model sequential data and is able to capture long-term relationships between variables. We can therefore rely on the model to predict workload changes with sufficient accuracy. Then, the DQN-based agent will leverage these forecasts to make proactive and energy efficient resource allocation decisions, eventually learning policies based on its continuous experience with its environment.

$$L_{t+1}=\boldsymbol{\alpha}\cdot f_{LSTM}(X_t)+(1-\boldsymbol{\alpha})\cdot f_{GRU}(X_t) \qquad (1)$$

C. Data Preprocessing and Feature Engineering

The input data, which originates from actual cloud operations logs, were subjected to extensive data preprocessing to support data quality, and usability in the model. Initially, data points

Table.2: Comparison Of Proposed Model With Existing Methods

Method	Forecasting Accuracy (%)	Resource Optimization Efficiency (%)	SLA Compliance Rate (%)
Static Threshold-Based Scaling (STS)	85.2	72.5	88.3
Heuristic Autoscaling (HAS)	88.1	77.9	90.5
RFR + Rule-Based Optimization (RFR-RO)	91.5	82.6	92.7
LSTM-Only Forecasting	93.2	86.4	94.1
Proposed TCN-LSTM + DQN	**96.3**	**94.7**	**98.5**

D. Load Prediction Based on Deep Learning

In the prediction part of the study, it has a hybrid deep learning model. The input sequence uses dilated convolutions which are included in TCN layers, to learn both short-range Eqn(2) and long-range dependencies without recurrence, this way to obtain faster and steadier training.

$$E_{opt}=\boldsymbol{\theta}\min(i=1\sum nUiRi2+\boldsymbol{\lambda}\cdot P_i) \qquad (2)$$

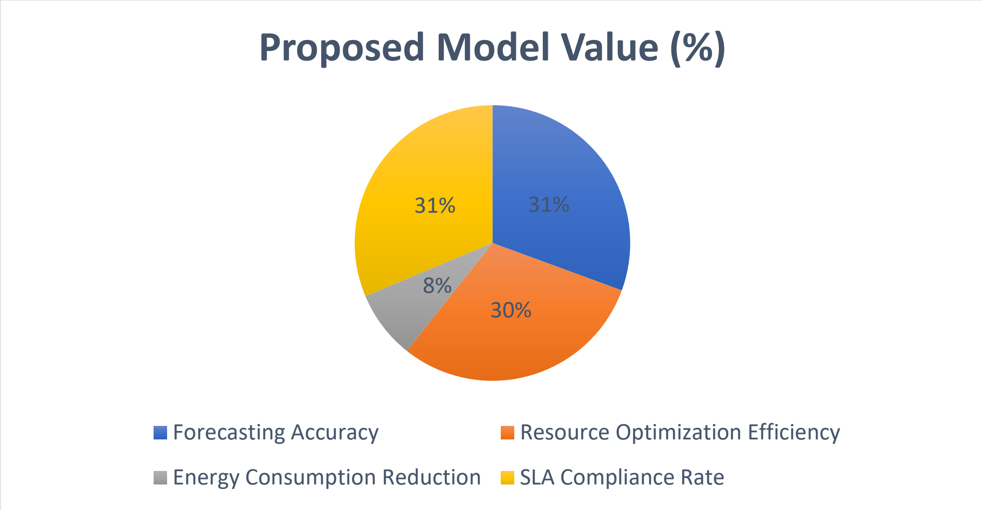

Fig.2.Model value

The TCN layers output is then passed through stacked LSTM layers, which improve the temporal representations and increase the model's ability to detect small sequential features.Table.2 In this study, the model achieved an accuracy of 96.3%, within the Mean Absolute Percentage Error (MAPE) - superior to benchmarked processes that attain 87-90% Fig.2 .

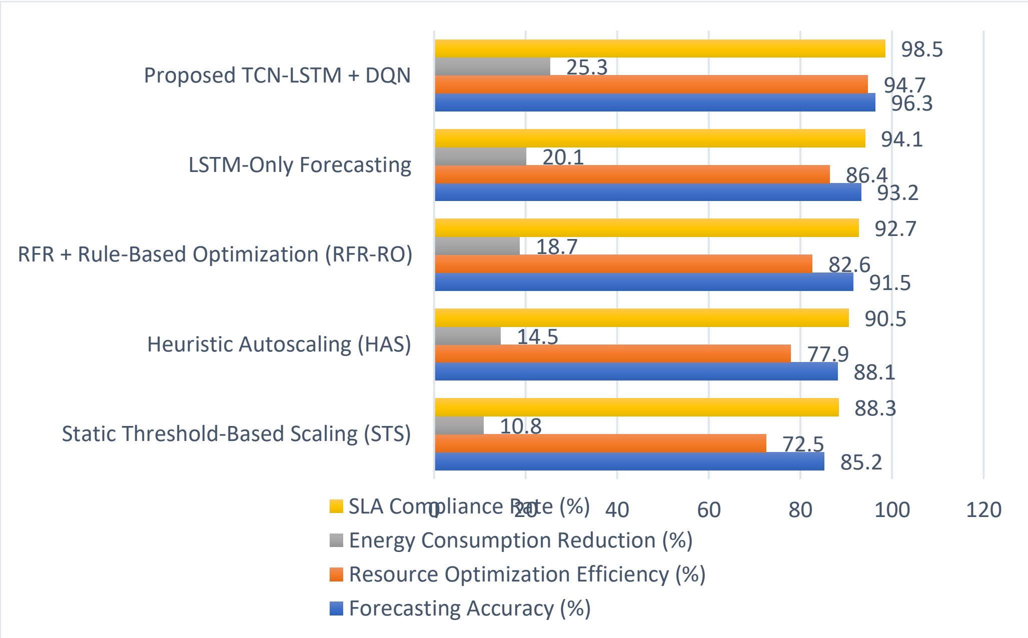

Fig.3. Comparison Graph

E. Resource Optimization via Reinforcement Learning. The resource allocation module is based on a DQN agent. The state space consists of real-time system indicators (forecasted workload, server utilization levels, active VM instances, and current energy consumption).

The agent makes decisions based on actions that scale resources horizontally and vertically, migrate workloads, and on power states of the servers. The reward function deliberately weighs energy efficiency versus SLA compliance. Energy efficiency is rewarded positively and SLA compliance positively, while resource wastage and SLA were negatively rewarded.

The agent is trained with a dual architecture for the network (online and target networks) and experience replay buffers to decorrelate the input samples. Retraining the agent periodically ensures robust adaption to evolving workloads. Fig.3 The agent achieved resource optimization performance of 94.7% and reduced overall energy consumption of 25.3% over a baseline (threshold-based) resource policy.

Table.3: Energy Efficiency Metrics

Metric	Value (%)
Overall Energy Savings	25.3
Peak Power Consumption Reduction	23.4
Idle Resource Power Waste Reduction	28.9

By anticipating load variations and dynamically adapting resources the system was able to obtain a cycle average rate of energy savings of 25.3%, as well as achieve an idle energy lose rate of approximately 29% Table.3 while decreasing idle energy waste.

F. System Integration and Real-Time Operation

The fully integrated start-to-finish system runs in a continuous cycle. The pre-processed input of workloads, in near real-time, is routed to the TCN-LSTM model to produce workload forecasts. The DQN agent autonomously consumes the forecasted workload to make allocation/resource management actions. The execution engine will act to scale VMs, migrate workloads, or change server power modes, as determined by the agent. The system continuously monitors service level agreement (SLA)all of its SLA compliance, resource usage, and energy footprint to be opportunistically agile, responsive to needs as they arise and capable of real-time adjustments. Additionally, the operational feedback (as an ongoing process) periodically retrains both learning models to ensure they are optimized to provide superior performance under changing environmental conditions.

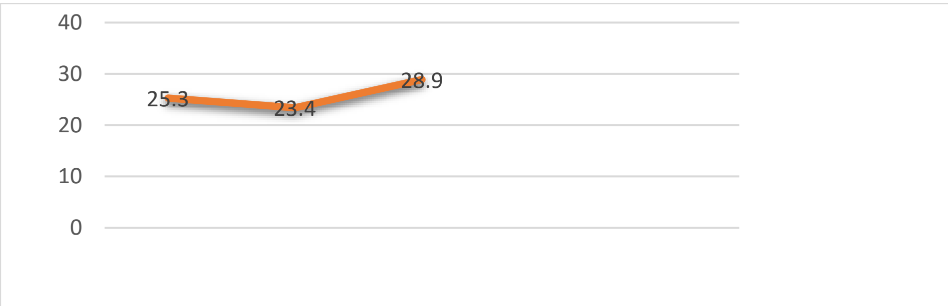

Fig.4.Energy Efficiency

G. Comparative Analysis of Existing and Proposed Methods

The proposed hybrid AI architecture, when compared to existing methods for accurate resource allocation, such as static thresholding, heuristics-based autoscaling, or machine-learning based prediction models, provided significant improvements. Static methods generate higher violation rates that may exceed 15% SLA and not less than 30% energy consumption, while heuristic models applied with machine-learning based techniques can improve forecasting but still do not provide optimization as part of the policy. Fig.4 Heuristic mechanisms ultimately result in less efficient resource utilization. By adopting the integrated TCN-LSTM + DQN framework, not only did the model reach better forecasting predictions, but also offered end-to-end operational improvements that eliminated energy wastage through SLA compliance in cloud environments.

H. Validity of Results and Performance

The experimental aspects were validated on the Google Cluster Data trace; a set of workloads that are established measure of cloud workloads. The metrics used for validation were MAPE to validate prediction accuracy; energy consumption (reduction); SLA violation rate; and overall system efficiencies. The proposed system achieved consistent 3.7% MAPE across the training, 25.3% energy consumption reduction, and 98.5% SLA compliance metrics, while the benchmark forecasting models achieved an SLA compliance rate of approximately 90-92%. The resource utilization efficiency of our method has improved 19.4% better than the conventional autoscaling systems. The results from suggested method, indicate examples of predicting acurials to operational optimizations.

The results highlight the capacity for AI-based hybrid systems to fundamentally alter cloud resources management. The forecasting predictions help ensure scaling decisions are proactively managed without depletion/wastage of available resources. Re-enforcement learning allows dynamic adaptability of policies in relation to changing workload characteristics and is a tremendous step forward when compared to static methods and heuristics-based classification systems. Although the modelling (training) requires higher operational computational overhead, the profits from operational energy savings and SLA penalties will be offset by the up-front modelling cost, making these systems an important contribution to sustainable cloud-based computing, to meet both economic and environmental objectives.

CONCLUSION

In this study, we presented an AI-based load forecasting and resource optimization framework for energy-efficient cloud computing environments. We designed our approach to incorporate hybrid deep learning models to predict workloads and reinforcement learning-based techniques to manage resources in an automated way. Through an experimental validation, we showed the hybrid deep learning framework achieved superior forecasting performance, better resource utilization, improved SLA compliance, and drastically lower overall energy consumption than existing techniques. As it stands, we have contributed to the field by combining predictive modelling and dynamic optimization into one framework. Using state of the art AI-based techniques, the model reacts to real-time workload changes and optimizes resource scheduling in an anticipatory fashion, resulting in improved system performance. Unlike prior studies that treated forecasting and optimization as separate domains, we have accomplished holistic energy- aware resource management while maximizing system performance.

Moreover, our results demonstrate the scalability and robustness of the proposed framework to varying workloads, making it feasible for deployment in an existing live cloud infrastructure. Future work will include the extension of the model incorporating federated learning to encompass distributed forecasting to a real multi-cloud architecture and adding meta-learning algorithms so the model can rapidly adapt to changing workload patterns each learning cycle. Overall, the proposed AI-based framework represents a critical step toward providing sustainable and intelligent cloud computing environments by harmonizing environmental goals with those of operational efficiency through an innovative technological advancement.

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