Journal of Global Research in Electronics and Communication
Volume 1, No. 12, December 2025
REVIEW PAPER

Optimization of Energy Usage in Data Centres Using AI Techniques

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***Abstract*—Data center energy optimization has come to be a very pressing research problem due to the active evolution of the digital infrastructure and the increasing environmental issues. The existing data centers are highly computing consuming cooling and power distribution thus high operational costs and carbon emission. The given paper examines the most critical energy consumption characteristics of data centers and discusses more advanced approaches to the AI to improve the energy-efficiency. It discusses AI-based models, such as deep learning, reinforcement learning, and hybrid optimization methods, in the predictive workloads, cooling strategies optimization and better power management. The hybridization of AI with the energy management system, edge-cloud architecture and smart monitoring systems is also discussed. It puts emphasis to performance measures such as the PUE, CUE and system reliability. Based on the findings, AI-based optimization of the next-generation data centers can be made much more energy efficient, robust, and sustainable.**

Keywords—Artificial Intelligence (AI), Data Centers, Energy Optimization, Machine Learning, Reinforcement Learning.

I. INTRODUCTION

Energy consumption is an urgent operational and environmental issue that modern data centers encounter as they run to accommodate the surging digital workloads of cloud computing (CC), big data analytics, and AI [1][2]. The high demands in computing resources, cooling facilities, and power supply system's demand high electricity in data centers. Intense power usage directly influences the cost of operation, stability of the system, and the emission of carbon; hence, data center operators have given attention to energy efficiency. The traditional energy management solutions are generally rigid and imprecise in addressing the dynamic, large scale, and complex nature of data center environments through the use of fixed control policies and heuristic optimization.

Artificial Intelligence (AI) is a powerful resource in respect to the efficient utilization of energy in the data centers, with the use of data-driven, adaptive, and forecasting decision-making [3][4]. Through machine learning, deep learning, and predictive analytics, AI techniques can include the nonlinear dynamics of the system, predict loads, optimize cooling and distribute power in a dynamically scheduling of computational resources [5]. These features enable data centers to minimize the amount of waste generated by energy, enhance energy proportionality, and be able to support performance and reliability at different workloads.

The coordination of IoT technologies also contributes to the optimization of AI in data centers regarding energy usage [6][7]. The IoT sensor nodes that are implemented on computing servers, cooling units and power distribution networks turn into sources of data in huge amounts and, in fact, heterogeneous data that are high-frequency and highly correlated [8]. This information is usually unstructured, sporadic, and evolving, and therefore requires effective processing at the edge and in cloud data centers [9][10].The AI-powered data fusion and edge-cloud analytics enable better system monitoring, real-time control, and intelligent energy management of data center infrastructure.

The review paper is dedicated to the analysis and the review of AI-driven methods of data center energy optimization, in which the particular attention is paid to the intelligent monitoring and predictive modeling techniques, as well as adaptive control strategy.

A. Structured of The Paper

The paper structured as follows: In Section II, the paper presents the energy consumption characteristics of data centers and identifies the major operational issues. Section III provides a detailed overview of artificial intelligence (AI) solutions for energy optimization. Section IV discusses the collaboration between AI and energy management systems to effectively monitor and control them. Section V provides a critical review of the available literature summarizing major findings and comparative insights. Lastly, Section VI summarizes the paper by presenting the key findings of the research and outlining possible avenues for future research.

II. ENERGY CONSUMPTION CHARACTERISTICS OF DATA CENTERS

The electrical grid is the usual source of power for data centers. Nonetheless, there are data centers that employ alternative power sources such as diesel, solar, wind, and hydrogen (fuel cells) [11]. In order to determine how much power each piece of IT hardware, infrastructure facility, and support system receives from outside sources, the total facility power is divided by the switchgear.

A. Power Distribution and Energy Flow in Data Centers

Data centers often use either static or dynamic uninterruptible power sources (UPSs) as part of their complicated multi-state power system (PSS). Reliability evaluation and the calculation method are both made more difficult by the complicated and idiosyncrasies of such a PSS's operation, even though PSS reliability may be assessed at both the design and reconstruction stages [12][13]. Typically, while deciding on the most sensible setup for the data center's PSS, the outcomes of a reliability calculation are useful.

Data centers are categorized by the Uptime Institute into four "Tier" levels of infrastructure, with the PSS configuration being one of the key factors. Providing a framework for creating a data center that achieves the targeted availability level is the primary goal of the tier classification [14]. Data centers are categorized according to their maintenance support capabilities and their capacity to endure a PSS failure. System availability determines the number of redundant components and parallel power supply lines in the PSS, which determines the reliability tier from I (the least reliable) to IV (the most reliable).

The carbon footprint of data centers is on the rise because of the substantial energy consumed to power their IT and cooling systems. In contrast, low emissions are another important factor in a data center's efficiency. The lower the greenhouse gas emissions, the more efficient a datacenter should be, not only working within a certain temperature range but also generating less carbon dioxide [15]. In this type of data center, all IT equipment, building systems, and everything else are planned to meet the requirements of being “green”. Consuming renewable energy sources is the main principle of green data centers.

B. *IT Load, Cooling Systems, and Infrastructure Energy Usage*

The cooling system's cold air is distributed through a plenum beneath the floor and perforated airflow panels in a typical data center that follows a hot aisle/cold aisle layout[16]. The chill air enters the narrow gaps between the servers from one side and exits the other, moving horizontally. The primary drawbacks are higher flow pressure dips and a combination of warm and cold air on the top side of the racks. Different cooling loads between racks are a consequence of the varied and unequal IT demands that most data centers operate under. When all server racks are supplied with cool air equally, hot spots cannot be avoided [17]. An on-demand distribution system for cold air across local cooling loads is necessary to avoid local overcooling while satisfying the cooling demands of individual computer racks. Uneven server use is seen in Figure 1 of a data center. Distributed airflow management is based on the idea of dividing a data center into sections and then controlling the airflow to each section according to its cooling needs.

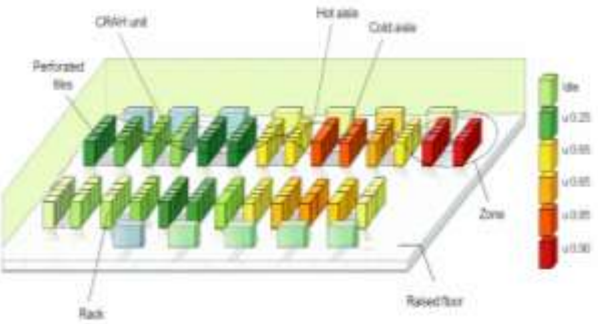

Fig. 1. A data center with uneven server utilization

C. *Energy Efficiency Metrics*

Data centers' energy efficiency is evaluated using the three main metrics: PUE, CUE, and WUE. The Green Grid pioneered the calculation of PUE, or power utilization efficiency, as a ratio of overall facility energy usage to that of IT equipment. PUE is a widely used metric for assessing data centers' energy efficiency; it was created by the Green Grid.

PUE is given an environmental context by CUE, which also monitors the carbon emissions linked to data center energy use [18]. Big data and cloud computing are two examples of the rapidly developing technologies that have resulted in an exponential rise in data communication and computation, increasing data center energy usage. The formula is the sum of all CO_2 emissions divided by the energy consumption of all IT equipment.

PUE is still the most popular and significant of these metrics in academia and business. Worldwide, a lot of work is being done to green the information and communication technology (ICT) industry. PUE variation is mainly caused by cooling systems, particularly in establishments that operate in warm or humid conditions.

Inefficient airflow design, static cooling setpoints, and outdated compressor or fan technologies often lead to overcooling or thermal imbalances, significantly inflating a data center’s PUE [19]. This inefficiency impacts energy bills and results in unnecessary carbon emissions and hardware degradation over time. Therefore, boosting all three efficiency measures simultaneously depends on optimizing cooling operations.

III. AI Techniques For Energy Optimization in Data Centers

Renewable energy systems are now more efficient than ever before because to artificial intelligence's revolutionary impact on predictive maintenance and energy optimization (see Figure 2). Power grid stability and energy management have become increasingly challenging due to the proliferation of renewable power sources, responsive loads, two-way power flow, and distributed energy resources (DERs) [20][21].

Fig. 2. Techniques of Artificial Intelligence

Instead, using AI and hybrid optimization techniques, as observed in Table I, it is now easy to develop responsive, leading and distributed methods for controlling energy systems [22][23]. AI-powered energy systems help predict energy usage, allocate resources, run and maintain batteries, connect microgrids, and regulate the dynamics of energy networks at all levels.

TABLE I. AI TECHNIQUES AND THEIR APPLICATIONS IN PREDICTIVE MAINTENANCE OF RENEWABLE ENERGY SYSTEMS

AI Technique	Description	Application in Energy Systems
Deep Learning	Learns complex patterns from large-scale, high-dimensional data	Early fault prediction and performance optimization
Convolutional Neural Networks (CNNs)	Extract spatial features from images and sensor data	Blade damage detection, component health monitoring
Recurrent Neural Networks (RNNs)	Model temporal dependencies in time-series data	Condition monitoring and trend forecasting
Long Short-Term Memory (LSTM)	Gather sequential data with long-term dependencies	Failure prediction and load/performance forecasting
Multi-Layer Perceptrons (MLPs)	Learn nonlinear relationships among system variables	Fault classification and efficiency prediction
Predictive Analytics	Uses statistical and ML methods to forecast future events	Maintenance scheduling and failure prevention

A. ML and DL-Based Energy Modeling and Prediction

The energy domain encompasses both a ML model for performance prediction and a building element energy retrofitting scenario. In addition, four other schematic predictive methodologies have been used to create energy forecasts. One of these methods, an ML method based on LSTM, promises to have quicker computing time than the Energy Plus simulation [24]. Alternatively, replaced a building energy modeling tool with an ML model that properly predicts thermal energy using a convolutional neural network (CNN) as an input, regardless of the building's design or the weather.

ML is one of the most reliable methods for evaluating building energy use, among other things, and for planning and forecasting the imminent rise in smart building energy efficiency [25]. Consequently, in order to enhance the effectiveness and efficiency of energy saving programs undertaken by building management teams, smart models are essential for smart building best practices [26]. Some of the ML methods used by building energy prediction models are DTs, k-NNs, support vector machines (SVMs), and others. A straightforward method for making predictions, the k-NN algorithm uses categorization. kNN is a simple, non-parametric learning technique for estimating building energy usage by classifying incoming data using an existing database.

B. Reinforcement Learning for Adaptive Energy Management

The capacity of deep neural networks to make adaptive decisions is combined with their capacity for generalization in Reinforcement Learning (RL). Electric car charging coordination, microgrid control, and renewable integration are some of the areas that have seen the implementation of algorithms like DDPG, SAC, and PPO [27]. While these studies demonstrate the promise of DRL in energy management, most focus on small-scale or simplified environments, often neglecting:

- Scalability to multi-node smart grids with complex topology.
- Robustness under high uncertainty and partial observability.
- Operational constraints such as reserve margins, ramping limits, and regulatory compliance.

RL is a branch of ML that provides a promising solution in this area since it allows machines to acquire optimal energy management strategies through the collaboration with the environment [28]. Contrary to the traditional optimization methods, RL uses the trial-and-error learning to dynamically adjust its policies. This real time learning and adaptation capability renders RL especially applicable in the management of the complexity of energy utilization in machines.

C. Hybrid AI Optimization for Energy-Efficient Data Center Operations

Solar energy system design and performance is optimized by AI-based optimization algorithms that include the ABC, PSO, and PIO. Among the specific advantages of these algorithms are strong abilities to search the globe, flexibility, and effective exploitation of high-fitness regions, which makes them highly relevant when it comes to the minimization of solar panel orientation, optimization of energy storage, fault detection, and optimization of large-scale solar arrays [29][30]. With the combination of these sophisticated algorithms, the solar energy systems able to become intelligent and adaptive networks that are constantly optimizing as the environment varies. The benefits of Hybrid AI-Optimization include:

- **Improved Predictive Accuracy:** It deals with the use of statistical procedures to enhance predictive validity. Hybrid AI-optimization risk models are more predictive and accurate since they integrate nonlinear predictive performance of the AI with the use of optimization algorithms to optimize the model behavior.
- **Stability and Robustness:** The complexity of AI models is controlled by regulating overfitting by imposing constraints on its parameters, complexity penalties, or, more importantly, by using domain-specific risk levels [31]. This is a tradeoff that is of special concern when false positives are of interest to be minimized and false negatives are to be avoided, e.g., credit risk rating, fraud detection and insurance underwriting.
- **Interpretability and Governance:** Hybrid models can be interpretable and controllable because they include explainable artificial intelligence features, such as feature importance analysis and SHAP-based explanations, and sensitivity analysis and scenario analysis through optimization. These functions provide clear and regulator-friendly reporting and are useful in aligning risk models in organisations with regulatory risk frameworks, including Basel III, IFRS 17 and Solvency II.
- **Improved Uncertainty Quantification:** Hybrid AI-optimization models also yield more precise risk measurements because of the inclusion of uncertainty estimation techniques (Bayesian modeling, bootstrapping and robust optimization). They give confidence limits, streamline systematic stress tests and set risk-adjusted decision boundaries, which enable decision-makers to make decisions under uncertainty with greater confidence.

IV. AI-INTEGRATED ENERGY MANAGEMENT SYSTEMS

A computer program called AI can be used in an energy management system to quickly and accurately process and evaluate data. It can also be used to predict how much energy used in the future, find strange patterns, and sort individual user load curves into groups [1]. There is a lack of practical experience in evaluating energy management systems powered by AI at this time [32]. Companies, particularly SMEs, are hesitant to use such systems for a number of reasons. These include insufficient knowledge of AI, concerns about the expense, and a lack of necessary resources and datasets.

A. Cloud-Based and Edge AI Solution

The number of IoT devices is growing very quickly, which means there is a huge amount of raw data that needs to be handled right now. Traditional cloud-native businesses are struggling to keep up with this boom due to rising latency, network congestion, and security issues. Decisions need to be made in real time in services like remote patient monitoring and self-driving automobiles, when delay might be fatal [33][34]. As a result of these changes, Edge-AI has been slowly replacing traditional AI. It enables processing with low latency close to the data source, at the network's edge. Figure 3 represents a comparison between AI CC and edge computing. Consequently, Edge-AI improves system responsiveness and saves bandwidth use by cutting down on the quantity of raw data that needs to be transferred to the cloud [35].

Fig. 3. Comparison b/w AI cloud and Edge computing

Advantages of Edge-AI: Edge nodes lack the processing capability of centralized cloud architecture, despite all its benefits. Complex AI models may demand more processing power than what edge devices can provide on their own. When it comes to supporting edge intelligence, cloud computing is the way to go [36]. Train AI models on the cloud, which provides a scalable platform for deploying deep learning and ML algorithms.

The benefits of both the cloud and the edge may be harnessed in a hybrid AI system through smart task distribution. Although compute-intensive operations like model retraining and large data analytics take place in the cloud, edge computing handles real-time inference and low-latency jobs. To address the limitations of existing Edge-AI solutions, it integrates the lightning-fast processing power of the edge with the cloud-based precision that is required[37].

B. Monitoring-AI and Control Architectures

Monitoring is made up of a number of tasks that are needed to prepare the data. Data collection is the primary concern of smart buildings, which encompasses a wide range of technologies such as smart sensors and smart meters set up at different levels (appliances, dwellings, buildings, etc.) or the combination of sensors to determine resident habits. The IoE is a distributed smart energy infrastructure that has recently arisen as a result of advancements in both device consumption and networked dispersed elements. It relies on the exchange of data between devices online [38]. Displayed in Figure 4 are the artificial intelligence methods employed for monitoring tasks in the investigated papers.

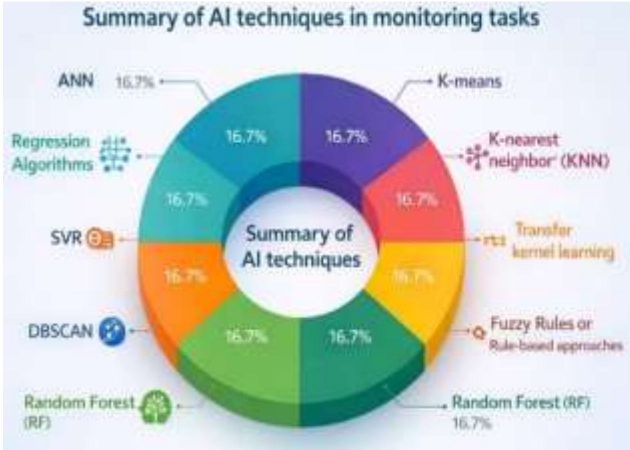

Fig. 4. Summary of AI techniques in monitoring tasks

In the process of gathering data, suggest a Smart EMS design with three parts. The data collection module is the initial part of the system and is responsible for sensing various kinds of data (including weather conditions), receiving status signals from units that produce or consume energy, and processing them. To prepare the data, the data fuser module finds outliers and missing data, and then uses a K-means clustering approach to find the centroids of each class to replace them. At last, it eliminates correlated characteristics by combining many variables to calculate new attributes based on their correlations.

V. Literature Review

Based on this literature review has shown that ML and DL models have a high value in enhancing load forecasting, predictive maintenance, and energy optimization in industrial and building energy systems. Complex architectures like LSTMs, CNNs, and composite models are superior to traditional ones and are more efficient in scheduling, grid stability, and operational stability.

Gaddala and Kollati (2025) The trends in AI, which are defining sustainable data centers, are geared towards optimization, predictive analytics, machine learning applications, and their implication on operational efficiency and environmental effects. Artificial intelligence (AI) has grown fast and has brought about a considerable effect on the operations of the data centers hence the need to adopt sustainable practices. The industry is being transformed by new trends like AI powered energy optimization, integration of solar energy and new cooling technologies. These inventions are to conserve energy as well as minimizing carbon footprints, and improving operation efficiency. With the help of AI, data centers are able to anticipate the maintenance requirements and optimize energy consumption as well as responsiveness to the real-time needs [39].

Baraskar (2025) The essential but unseen components of contemporary artificial intelligence are the hundreds of processors, graphics processing units (GPUs), and accelerators that are integrated into every single gadget on Earth. This includes cars, refrigerators, printers, phones, social networks, and more. Many people and the economy have to pay a heavy price for this computer revolution. Information technology data centers that house artificial intelligence are among the most power-hungry parts of the network. Data handling and storage, as well as dissipating the enormous amounts of heat produced, need twenty-four-hour electricity. Carbon emissions increase with each use, putting a burden on power grids throughout the world and adding to climate change. Wherever else power generation is still dependent on fossil fuels, the environmental toll is disproportionately high [40].

Khurram and Hussain (2024) conversation about how the coming together of quantum algorithms, renewable energy integration into data centers, and art AI revolutionize energy use management and cybersecurity. By utilizing quantum algorithms, data centers may maximize the usage of renewable energy sources such as solar and wind while minimizing the use of traditional, non-renewable sources. Quantum algorithms make prediction more precise, optimize energies more efficiently in real-time and balance loads, which make data centers more energy efficient and resistant [41].

Goble (2023) the application of AI to enhance sustainability in cloud data centers, in particular, to optimize energy, balance workloads, and use smart cooling systems. The adoption of AI in cloud computing infrastructure is a chance of attaining long-term sustainability and carbon neutrality. The purpose of AI in sustainable cloud computing is critical in exploiting energy issues around the world and creating a digital ecosystem based on intelligence and green cooling options. The automation made by AI gives cloud providers the ability to predict and deal with the energy inefficiencies and minimize waste and increase the overall system reliability [42].

Kumar, Khatri and Diván (2022) The need for data center hosting is on the rise due to the growing computation and storage demands of cloud services platforms and information technology (IT). This, in turn, leads to a growth in the demand for energy, which is needed to power the IT devices and cool the data center. The increasing demands placed on data center facilities have made it more difficult to optimize power usage without compromising data center energy quality [43].

Suryadevara (2021) Energy-proportional computing focuses on the efforts to reach the most efficient energy usage in data centers, where the workload is directly related to the energy consumption. It discusses the concepts and practical applications of energy-proportional data center computing. Design principles such as energy-conscious scheduling, adaptive resource allocation, and dynamic power management are studied [44].

Table II is a summary of AI-based sustainable data center energy management, including optimization strategies, efficiency benefits, environmental concerns, and future trends of more green, intelligent infrastructure.

TABLE II. AI-BASED TECHNIQUES FOR SUSTAINABLE DATA CENTER ENERGY MANAGEMENT

Authors (year)	Focus Area	Key Findings	Approaches	Objectives	Future Work
Gaddala & Kollati (2025)	AI-driven sustainable data center operations	AI significantly enhances operational efficiency and reduces environmental impact through intelligent optimization and predictive analytics	Machine learning–based energy optimization, predictive maintenance, real-time workload adaptation	Improve energy efficiency, reduce carbon footprint, and enhance the sustainability of data centers	Integration of advanced AI models with large-scale renewable energy systems and autonomous decision-making frameworks
Baraskar (2025)	Environmental and economic impact of AI data centers	Data centers that house artificial intelligence need a lot of electricity, which puts a strain on the grid and causes carbon emissions to rise, particularly in areas that rely on fossil fuels.	Large-scale CPU/GPU/accelerator-based computing infrastructure analysis	Highlight the sustainability challenges and energy consumption risks of AI-driven infrastructures	Development of greener AI hardware, energy-aware AI workloads, and policy-driven sustainability frameworks
Khurram & Hussain (2024)	AI, quantum computing, and renewable energy integration	Quantum algorithms can significantly improve renewable energy utilization, forecasting accuracy, and cybersecurity in data centers	Quantum algorithms for energy optimization, load balancing, and renewable energy forecasting	Improve sustainability, resilience, and energy efficiency while decreasing use of fossil fuels.	Practical deployment of quantum–AI hybrid systems and scalability evaluation in real-world data centers
Goble (2023)	AI-enabled sustainability in cloud data centers	AI improves workload balancing, intelligent cooling, and energy optimization, supporting carbon-neutral cloud operations	Deep learning, automation, real-time analytics, intelligent cooling mechanisms	Achieve long-term sustainability and carbon neutrality in cloud computing	Quantum computing and AI integration and cloud orchestration with renewable energy in mind
Kumar, Khatri & Diván (2022)	Power efficiency optimization in data centers	Machine learning-based techniques effectively improve power usage effectiveness (PUE) without compromising energy quality	ML-based power optimization, energy quality monitoring, and intelligent control systems	Optimize power usage and ensure reliable energy quality under increasing IT workloads	Adaptive and real-time ML models for heterogeneous and large-scale data center environments
Suryadevara (2021)	Energy-proportional computing in data centers	Energy consumption can be aligned proportionally with workload through dynamic resource and power management	Agile resource allocation, virtualization, consolidation, and energy-aware scheduling are all aspects of dynamic power management.	Achieve optimal energy efficiency and reduce energy wastage	Integration of energy-proportional techniques with AI-driven predictive control and next-generation cooling technologies

VI. CONCLUSION AND FUTURE WORK

Energy optimization in data centers using AI techniques. The exponential growth of computing workloads in today's data centers is causing significant problems, such as excessive energy usage, high operational expenses, and negative effects on the environment. Adaptive and predictive methods for managing energy usage are offered by AI-based solutions, as demonstrated in the review. These solutions include ML, DL, RL, and hybrid AI-optimization algorithms. These techniques facilitate predictions of loads with high accuracy, intelligent control of the cooling process, dynamic resource scheduling, and enhancement of energy proportionality reducing the amount of energy wasted as well as the performance and reliability of the system. Additionally, the IoT and edge-cloud AI systems will enhance real-time monitoring and data interconnection and control to create scaled and responsive energy management systems. Overall, the findings support the belief that AI-driven energy management is a significant instrument in improving the efficiency, sustainability, and resilience of data center operations, which are one of the enablers of green and smart data centers.

Further studies are required on mass real-life implementation of AI-based energy management systems, combination with renewable energy sources and carbon-conscious scheduling and the exploitation of explainable and trustworthy AI. Besides, studying quantum-AI hybrids and framework benchmarking can also increase scalability and adoption.

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