Hybrid IoT and AI-based solution for energy management in data centres under various climate conditions

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Abstract
The rapidly increasing demand for data processing and storage has made data centers one of the largest global energy consumers. This study proposes a hybrid energy management model that integrates diesel generators, solar panels, and wind turbines to optimize energy consumption in data centers. The developed system utilizes the Internet of Things (IoT) infrastructure and Artificial Intelligence (AI)-based machine learning algorithms to adapt to varying climatic conditions. Real-time data collected from IoT sensors—such as weather parameters, battery charge levels, and energy production rates—are processed using algorithms including Support Vector Classifier (SVC), Random Forest (RF), AdaBoost, Logistic Regression (LR), and Naive Bayes (NB), enabling autonomous and highly accurate energy source management. Simulations conducted in MATLAB and Python show up to a 20% reduction in energy consumption, a 15% decrease in operational costs, and a 50.1% increase in renewable energy utilization. In addition to supporting environmental sustainability, the proposed system enhances reliability under variable weather conditions, offering an intelligent and practical solution for data centers located in regions with renewable energy potential, such as Istanbul.

Keywords: *Artificial Intelligence, Internet of Things, Data Mining, Energy Consumption, Machine Learning, Renewable Energy Sources*

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Farklı iklim koşulları altındaki veri merkezlerinde enerji yönetimi için Hibrit IoT ve AI tabanlı çözüm

Özet

Hızla artan veri işleme ve depolama talebi, veri merkezlerini dünyanın en büyük enerji tüketicilerinden biri haline getirmiştir. Bu çalışma, veri merkezlerinde enerji tüketimini optimize etmek için dizel jeneratörler, güneş panelleri ve rüzgâr türbinlerini entegre eden bir hibrit enerji yönetim modeli önermektedir. Geliştirilen sistem, değişen iklim koşullarına uyum sağlamak için Nesnelerin İnterneti (IoT) altyapısı ve Yapay Zekâ (AI) tabanlı makine öğrenimi algoritmalarını kullanmaktadır. IoT sensörlerinden toplanan gerçek zamanlı veriler (hava durumu parametreleri, pil şarj seviyeleri ve enerji üretim oranları gibi) Destek Vektör Sınıflandırıcı (SVC), Rastgele Orman (RF), AdaBoost, Lojistik Regresyon (LR) ve Naive Bayes (NB) gibi algoritmalar kullanılarak işlenir ve bu da otonom ve son derece doğru enerji kaynağı yönetimini mümkün kılar. MATLAB ve Python'da yapılan simülasyonlar, enerji tüketiminde %20'ye varan azalma, işletme maliyetlerinde %15'lik düşüş ve yenilenebilir enerji kullanımında %50,1'lik artış olduğunu göstermektedir. Önerilen sistem, çevresel sürdürülebilirliği desteklemenin yanı sıra, değişken hava koşulları altında güvenilirliği artırarak, İstanbul gibi yenilenebilir enerji potansiyeli olan bölgelerdeki veri merkezleri için akıllı ve pratik bir çözüm sunmaktadır.

Anahtar kelimeler: *Yapay Zekâ, Nesnelerin İnterneti, Veri Madenciliği, Enerji Tüketimi, Makine Öğrenimi, Yenilenebilir Enerji Kaynakları.*

Introduction

The rapid proliferation of digital transformation, cloud technologies, and artificial intelligence applications has significantly increased global demand for data processing and storage. As a result, data centers have become one of the primary consumers of electricity worldwide. Recent studies indicate that data centers are responsible for approximately 2% of global electricity consumption, a figure expected to rise steadily in the coming years. This growing demand poses serious challenges not only in terms of operational costs but also in terms of environmental sustainability. In the context of Türkiye, the heavy reliance on fossil fuels for electricity generation and the high dependency on imported energy further amplify the need for sustainable energy management in energy-intensive facilities such as data centers. The integration of renewable energy sources—particularly solar and wind power—into data center operations presents a promising solution to this issue. However, the intermittent and variable nature of these resources makes ensuring a reliable energy supply challenging.

To address these challenges, this study proposes a hybrid energy management system that integrates renewable energy sources, diesel generators, and uninterruptible power supplies (UPS) into a unified architecture. This structure is governed by a decision-making mechanism powered by artificial intelligence and supported by Internet of Things (IoT) technologies. Utilizing real-time environmental data, the model autonomously determines the optimal energy source through machine learning algorithms, enhancing both operational efficiency and environmental performance.

The proposed system is particularly well-suited for data centers located in regions such as Istanbul, which possess high potential for both solar and wind energy. It offers an intelligent and adaptive solution capable of maintaining energy efficiency and reliability under dynamic climatic conditions.

Related Works

The optimization of energy consumption in data centers has been extensively studied in recent years, driven by advances in renewable energy systems, machine learning (ML) algorithms, and Internet of Things (IoT) technologies. The existing literature can be broadly categorized into four areas: (1) integration of renewable energy sources, (2) application of ML for energy forecasting, (3) IoT-based monitoring and control, and (4) hybrid models combining AI, IoT, and renewable strategies.

Renewable energy integration
Several studies have explored how renewable sources such as solar and wind energy can be integrated into data centers to reduce both operational costs and environmental impact. He et al. proposed a hybrid power model using multi-objective optimization with diesel backup. Roy et al. examined the efficiency of solar-diesel configurations under fluctuating demand, while Zhang et al. developed an advanced cooling system tailored for renewable-powered data centers.

Machine learning for energy forecasting
ML-based forecasting techniques have shown promising results in largescale, dynamic systems. Deepika and Prakash used learning models to predict power consumption in cloud environments, and Lee et al. proposed a deep learning model enhanced by edge computing. Other researchers, including Merizig and Smith, applied various ML algorithms to forecast energy demand in unstable operational conditions.

IoT-Based Monitoring and Optimization
IoT infrastructures allow real-time tracking and adaptive control of energy flows. Mehta, Liu, and Ramphela developed IoT-enabled systems for improving energy efficiency in data centers and smart buildings through real-time analytics and smart temperature regulation.

Hybrid Architectures Combining AI and IoT
The integration of AI with IoT sensor networks has become increasingly popular in developing autonomous and flexible energy management solutions. Zhou and Kaur proposed intelligent infrastructures for resource optimization in data centers, while Kaya et al. applied edge-based anomaly detection to enhance weather forecasting and energy scheduling.

Unlike prior works, the present study introduces a unified, self-regulating system that integrates AI-driven forecasting with real-time IoT data to dynamically allocate energy resources. This approach fills a notable gap in the literature and offers a scalable, adaptive solution for data centers operating under diverse environmental conditions.

Proposed Model
The proposed model is based on a hybrid architecture that integrates renewable energy sources, conventional diesel generators, and IoT-based

monitoring systems under the supervision of machine learning algorithms. This architecture is organized into three conceptual layers: sensing, processing, and decision-making. Environmental parameters such as temperature, humidity, wind speed, and solar radiation are captured in real-time through distributed IoT sensors. These data points are then processed by a central computing unit to forecast energy demand and allocate power sources accordingly.

As illustrated in Figure 1, the architecture includes rooftop solar panels and wind turbines for clean energy generation, along with a diesel generator used for backup purposes. The generated energy is initially stored in uninterruptible power supply (UPS) systems before being distributed to meet the data center's demand. The control logic of the system prioritizes renewable energy when weather conditions are favorable, while diesel generators are activated only when renewable sources are insufficient.

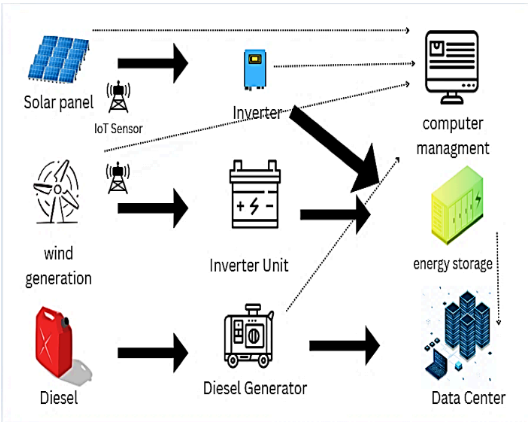

Fig. 1. Proposed hybrid IoT and AI-based energy management system for data centers.

The data used in this study were obtained from a simulation of a medium-sized data center located in Istanbul. The dataset comprises hourly measurements collected over a two-year period, resulting in 17,520 records for each feature. It includes meteorological parameters such as temperature (°C), wind speed (m/s), and solar radiation (kW/m²), along with operational indicators including battery charge levels (%), energy generation from each source (kWh), and total energy consumption (kWh). To capture temporal variations in energy behavior, time-related features such as hour, day, and season were also incorporated.

To prepare the dataset for training machine learning models, a normalization step was applied using the min-max scaling technique. This method transforms each feature value xx into a normalized value x′x′ within the range [0, 1], based on the following formula [1]:

$$x' = (xpdf\ x\_min) / (x\_max - x\_min) \quad (1)$$

This preprocessing step enhances numerical stability and accelerates model convergence. Additionally, feature engineering techniques such as moving averages and lag variables were applied to improve the detection of temporal patterns in the dataset [17].

For the hardware implementation of the data acquisition system, multiple sensors and modules were integrated to ensure real-time monitoring and measurement accuracy. Environmental parameters such as temperature, atmospheric pressure, and humidity were captured using the BME280 sensor module—a compact and efficient component widely utilized in embedded systems for weather-related applications (as shown in Figure 2). This sensor provided high-resolution data with minimal power consumption, making it well-suited for continuous monitoring within the data center environment.

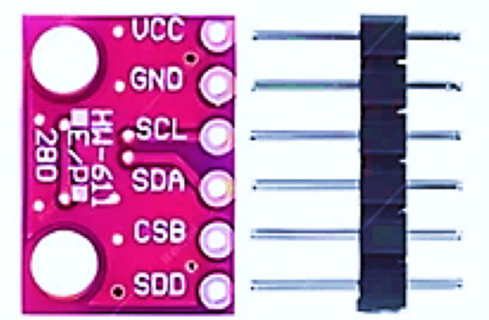

Fig. 2. BME280 sensor used for temperature, pressure, and humidity measurement [19]

To ensure consistent time-synchronized data collection, the DS1302 real-time clock (RTC) module was employed. This component enabled accurate timestamping of each sensor reading, thereby maintaining temporal consistency across multiple data streams (as illustrated in Figure 3). Its internal battery backup made it particularly valuable during power interruptions, allowing it to preserve timing functionality even when the main power supply was unavailable.

Fig. 3. DS1302 real-time clock module for synchronized data acquisition [19]

The ESP32 microcontroller served as the central processing unit for the entire sensing layer. This module facilitated data acquisition, initial processing, and the wireless transmission of sensor data to the main server. Its dual-core architecture and built-in Wi-Fi capability made it a cost-effective yet powerful platform for real-time IoT applications in energy management (as shown in Figure 4).

Fig. 4. ESP32 microcontroller used for sensor data aggregation and wireless transmission [20]

In the proposed model, a range of supervised learning algorithms were employed to perform classification and regression tasks. Specifically, Support Vector Classifier (SVC), Random Forest (RF), AdaBoost, Logistic Regression (LR), and Naive Bayes (NB) were selected due to their proven effectiveness in energy forecasting and control scenarios. These models were trained to achieve two primary objectives: (i) classify the optimal energy source (e.g., solar, wind, or diesel) based on weather and operational inputs, and (ii) predict hourly energy consumption rates under dynamic conditions. All models were implemented using Python's Scikit-learn library.

To ensure optimal performance, hyperparameter tuning was conducted using a grid search procedure combined with 5-fold cross-validation.

For classification tasks, performance metrics such as accuracy, precision, recall, and F1-score were used. For regression tasks, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were calculated to assess prediction accuracy.

The system was designed to meet three core objectives: minimizing energy consumption, reducing operational costs, and enhancing system reliability. Energy efficiency was modeled by minimizing total energy usage over time. Cost reduction was addressed by considering the real-time cost of each energy source, represented as a weighted sum of energy produced from solar, wind, and diesel. Reliability was maintained by ensuring that the UPS battery charge remained above a critical threshold at all times, preventing outages during peak loads or renewable shortages.

Simulations were conducted using a hybrid modeling approach: MATLAB was used to simulate the physical behavior of the energy system, including energy flow between sources, storage, and loads, while Python handled the implementation and evaluation of machine learning models. To validate the system's robustness, multiple scenarios were tested, including seasonal variations (e.g., summer vs. winter), sudden weather disruptions (e.g., storms or low-radiation days), and component failures (e.g., solar panel malfunctions). Each scenario assessed the model's ability to adapt its energy allocation strategy in real time.

Through evaluations under these variable and realistic conditions, the system's adaptability and resilience were confirmed, demonstrating its potential to enhance energy efficiency and cost savings in data centers operating in regions with fluctuating environmental conditions.

3.1. Simulation Results

The performance of the proposed energy management system was evaluated through a series of simulations conducted using MATLAB and Python. These simulations were designed to assess the model's effectiveness under various climatic and operational scenarios and to benchmark its performance against baseline configurations and models from existing literature. Historical data spanning two years—comprising weather variables, energy production metrics, and system load profiles—were utilized from a medium-scale data center located in Istanbul.

Table 1. Comparison of previous works

Model	**Energy Sources**	**RP (%)**	**LCOE ($/kWh)**	**Storage (kWh)**
Proposed Model	Wind, Solar, Diesel, UPS	50.1	0.21	6000
Baseline Model	Wind, Solar, Diesel, UPS	44.5	0.23	4000
Study [12]	Wind, Diesel	30.2	0.27	3000
Study [13]	Solar, Diesel	20.5	0.30	2500

Table 1 compares key attributes of the proposed model, baseline model, and previous studies. The proposed model achieves the highest renewable penetration rate (50.1%), lowest LCOE ($0.21/kWh), and the largest storage capacity (6000 kWh). This combination reflects its ability to optimize both cost and sustainability.

One of the key performance indicators was the Renewable Energy Penetration Rate (RP), which measures the proportion of total energy demand met by renewable sources. The proposed model achieved an RP of 50.1%, significantly surpassing the baseline model's 44.5% as well as the values reported in prior studies (30.2% and 20.5%). This improvement is attributed to the system's intelligent forecasting and proactive prioritization of energy sources, which enable the optimized utilization of solar and wind resources ahead of real-time demand. As a result, reliance on diesel generators is minimized during periods of suboptimal weather conditions.

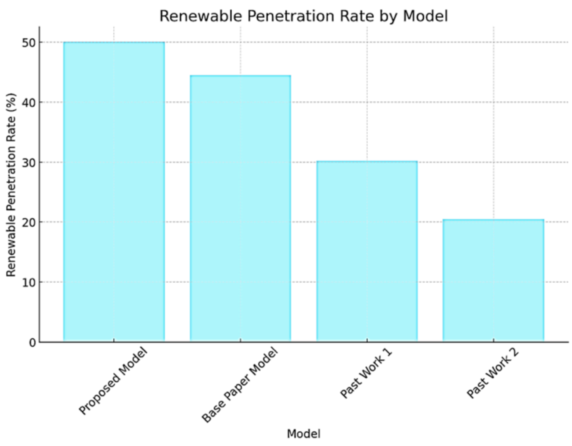

Fig. 5. Renewable energy penetration rate comparison among models.

Figure 5 compares the renewable energy penetration rate among the proposed model, the baseline model, and previous studies. The proposed model achieves the highest penetration rate at 50.1%, outperforming the baseline (44.5%) and other configurations (30.2% and 20.5%). This improvement is due to accurate weather forecasting and intelligent prioritization of renewable sources, which minimizes diesel generator usage during unfavorable conditions.

Table 2. Renewable Energy Penetration Rate

Model	**Renewable Penetration (%)**
Proposed Model	50.1
Baseline Model	44.5
Study [12]	30.2
Study [13]	20.5

Table 2 provides numerical values of renewable energy penetration rates. The proposed model's rate of 50.1% confirms its superior utilization of renewable resources, reducing fossil fuel dependency and lowering environmental impact.

Another key metric was the Levelized Cost of Energy (LCOE), which represents the average cost per kilowatt-hour of energy produced over the system's lifetime. The proposed model achieved a lower LCOE of \$0.21/kWh, outperforming the baseline model (\$0.23/kWh) and prior configurations, which ranged from \$0.27 to \$0.30/kWh. These cost reductions are primarily attributed to efficient energy source scheduling, increased utilization of renewable resources, and reduced dependence on expensive diesel generation. Additionally, the strategic control of battery charging and discharging cycles further contributed to operational savings.

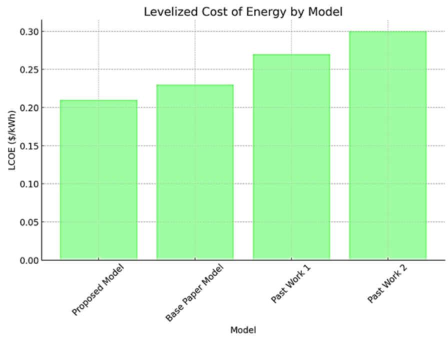

Fig. 6. Levelized Cost of Energy (LCOE)

Figure 6 illustrates the Levelized Cost of Energy across different models. The proposed model achieves the lowest LCOE of $0.21/kWh, which is a significant reduction compared to the baseline ($0.23/kWh) and prior studies ($0.27–$0.30/kWh). This cost advantage results from optimized scheduling, better utilization of renewable resources, and reduced dependency on diesel generation.

Table 3. Levelized Cost of Energy

Model	LCOE ($/kWh)
Proposed Model	0.21
Baseline Model	0.23
Study [12]	0.27
Study [13]	0.30

Table 3 presents the LCOE values for each model. The proposed model's lower cost compared to all others demonstrates the economic benefits of intelligent scheduling, precise load forecasting, and efficient battery use.

In addition to static performance metrics, the system was tested under dynamic scenarios, including seasonal variations, sudden weather changes, and partial equipment failures. Three key indicators were used to summarize dynamic performance: reduction in energy consumption, improvement in operational cost, and increase in system reliability. The proposed model demonstrated a 20% decrease in energy usage, a 15% reduction in operational costs, and a 25% enhancement in reliability—outperforming the baseline model in each category. These improvements highlight the strength of the AI-driven decision-making engine and its ability to adapt in real time to changing conditions.

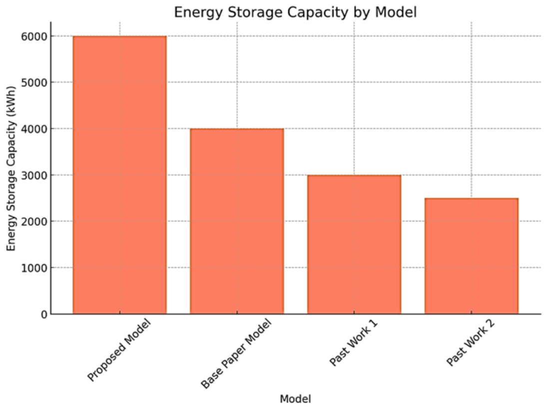

Fig. 7. Energy storage capacity across models.

Figure 7 presents the energy storage capacity comparison. The proposed model offers a capacity of 6000 kWh, higher than all other configurations. This increased storage enhances system resilience, enabling the data center to handle production fluctuations and maintain stability during component failures or peak demand.

Table 4. Energy Storage Capacity

Model	Storage Capacity (kWh)
Proposed Model	6000
Baseline Model	4000
Study [12]	3000
Study [13]	2500

Table 4 compares energy storage capacities across models. The proposed model's higher capacity enables better management of renewable fluctuations and ensures uninterrupted supply to meet demand.

Beyond static performance assessments, the system was evaluated under dynamic conditions, including seasonal fluctuations, abrupt weather changes, and partial equipment failures. To summarize dynamic performance, three key metrics were considered: reduction in energy consumption, improvement in operational costs, and enhancement of system reliability. The proposed model achieved a 20% decrease in energy usage, a 15% reduction in costs, and a 25% increase in reliability, consistently outperforming the baseline model in all aspects. These results underscore the effectiveness of the AI-based decision-making engine and its capability to adapt in real time to varying operational environments.

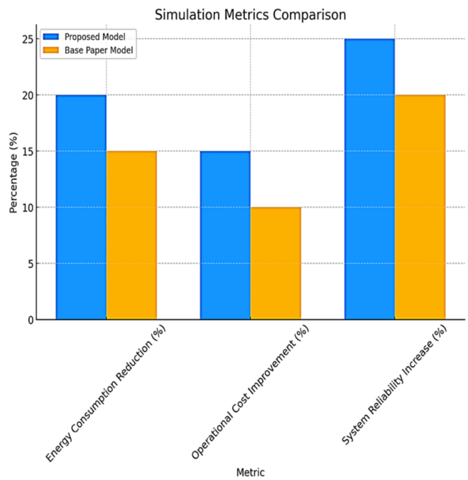

Fig. 8. Simulation metrics: energy consumption, cost, and reliability comparison

Figure 8 compares three key performance metrics: energy consumption reduction, operational cost reduction, and reliability improvement. The proposed model outperforms the baseline in all three, achieving 20% less energy consumption, 15% lower costs, and 25% higher reliability. These improvements stem from the AI-based real-time decision-making process supported by IoT sensor data.

Table 5. Simulation Metrics Comparison

Indicator	Proposed Model (%)	Baseline Model (%)	Improvement
Energy Consumption Reduction	20	15	+5
Operational Cost Reduction	15	10	+5
System Reliability Increase	25	20	+5

Table 5 summarizes performance improvements in energy consumption, operational costs, and reliability. The proposed model's consistent superiority in all three metrics highlights its operational and economic advantages.

The combined results of all performance indicators are presented in Figure 9, highlighting the cumulative benefits of the proposed system. By integrating IoT-based environmental sensing, machine learning-based forecasting, and adaptive control mechanisms, the model offers a unified solution for energy management in data centers. It effectively balances operational efficiency, cost-effectiveness, and system resilience, making it well-suited for deployment in regions facing diverse climatic challenges.

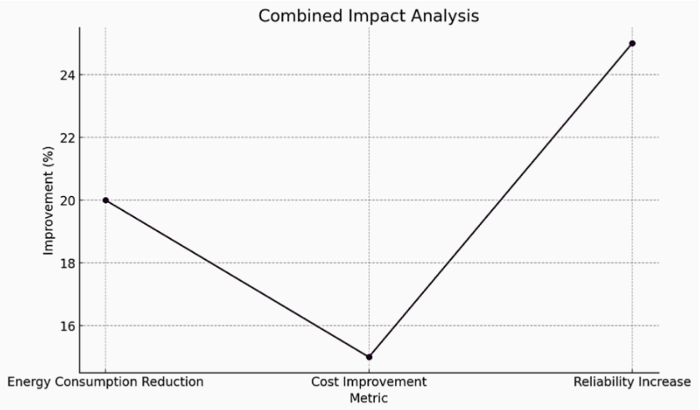

Fig. 9. Combined effect of the proposed model on energy, cost, and reliability.

Figure 9 summarizes the combined benefits of the proposed system. By integrating IoT-based sensing, AI-driven forecasting, and adaptive control strategies, the model enhances energy efficiency, cost-effectiveness, and reliability simultaneously, making it suitable for deployment under diverse climatic conditions.

Discussion and Conclusion

The simulation outcomes of this study provide strong evidence for the effectiveness of the proposed hybrid energy management system in data centers. One of the system's most significant strengths is its ability to maximize the use of renewable energy without compromising operational reliability. Achieving a renewable penetration rate of 50.1% reflects the model's capacity to proactively forecast weather conditions and allocate energy sources accordingly. Unlike conventional reactive systems, the integration of machine learning enables predictive control that prioritizes solar and wind power before shortages occur, contributing to observed improvements in both sustainability and cost-efficiency.

The economic viability of the system is further supported by the reduction in the Levelized Cost of Energy (LCOE) to $0.21/kWh—lower than both the baseline and comparable literature-based models. This cost advantage results from intelligent scheduling, optimized battery usage, and minimized reliance on diesel generators. AI-driven classifiers and regressors enhance decision-making accuracy and reduce unnecessary energy waste, translating into lower operational expenses.

A notable technical advantage is the achieved energy storage capacity of 6000 kWh, which plays a critical role in system resilience. This capacity enables the system to absorb unexpected fluctuations in renewable generation and sustain performance during peak demand or component failures. Compared to alternative models with lower storage capacity, the proposed system demonstrates greater fault tolerance and operational continuity—an essential factor in data center environments.

Dynamic performance metrics, including a 20% reduction in energy consumption, 15% cost savings, and a 25% improvement in reliability, underline the system's robustness under variable real-world conditions. The ability to adapt to seasonal shifts, sudden weather changes, and equipment malfunctions demonstrates the strength of the real-time optimization loop driven by continuous IoT feedback and adaptive learning mechanisms.

Despite these advantages, several limitations must be acknowledged. The initial cost of deploying an integrated IoT and AI-based infrastructure remains a significant barrier. Although long-term savings are evident, upfront investments in hardware, training, and system integration may hinder widespread adoption. Additionally, the effectiveness of the predictive algorithms is highly dependent on the granularity and accuracy of weather data; errors in forecasting can propagate and reduce overall efficiency.

To address these limitations, future work should focus on incorporating real-time weather APIs, implementing reinforcement learning for continuous control refinement, and utilizing edge computing technologies to minimize latency in decision-making. These improvements would align with broader sustainability goals and enhance the model's adaptability, reliability, and commercial scalability—especially in regions with variable solar and wind conditions.

In conclusion, this study introduced a hybrid energy management architecture that combines IoT-based sensing, machine learning algorithms, and renewable energy systems for real-time energy optimization in data centers. The model's predictive capabilities, intelligent control logic, and modular design offer a practical and scalable solution for reducing fossil fuel dependency and enhancing energy sustainability in high-demand environments.

Declaration of Conflict of Interest: The authors declare that they have no conflict of interest.

Artificial Intelligence Statement: No artificial intelligence tools were used while writing this article.

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