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RESEARCH ARTICLE RENEWABLE ENERGY

Power and Carbon Footprint Evaluation and Optimization in Transitioning Data Centres

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ABSTRACT

Data centers are among the largest consumers of energy and significant contributors to global carbon emissions. This paper presents a comparative evaluation of two mathematical energy consumption models—the linear and cubic models—within a simulated cloud data center environment using the CloudSim toolkit. Key performance indicators were analyzed, including total energy consumption, carbon dioxide (CO_2) emissions, cost, power usage effectiveness (PUE), carbon usage effectiveness (CUE), response time (latency), and packet loss, under varying workload conditions.The cubic model demonstrated greater sensitivity to workload fluctuations and more accurately captured the dynamics of energy consumption in high-utilization environments, while the linear model offered computational simplicity and conservative estimates. The integration of 50% renewable energy sources led to substantial reductions in both emissions and operational costs. Specifically, the linear model recorded a 33.3% reduction in CO_2 emissions, a 71.5% improvement in CUE, and a 15.4% decrease in cost, while the cubic model achieved a 33.3% reduction in CO_2 emissions, a 23.2% improvement in CUE, and a 24.6% decrease in operational cost—demonstrating the effectiveness of clean energy adoption without compromising system performance or service quality.

تقييم وتحسين الطاقة والبصمة الكربونية في مراكز البيانات في مرحلة الانتقال نحو الاستدامة

إيمان المهدي [1]، غزلان بن مسكين [2]

الكلمات المفتاحية

كفاءة الطاقة
تحليل استهلاك الطاقة
الطاقات المتجددة
نموذج الطاقة الخطي
نموذج الطاقة التكعيبي

الملخص

تُعد مراكز البيانات من بين أكبر المستهلكين للطاقة ومصادرًا رئيسية لانبعاثات الكربون على مستوى العالم. تقدم هذه الورقة تقييمًا مقارنًا بين نموذجين رياضيين لاستهلاك الطاقة—النموذج الخطي والنموذج التكعيبي ضمن بيئة محاكاة لمركز بيانات سحابي باستخدام أداة **CloudSim**. تم تحليل مؤشرات الأداء الرئيسية، مثل إجمالي استهلاك الطاقة، وانبعاثات ثاني أكسيد الكربون، والتكلفة، وكفاءة استخدام الطاقة (PUE)، وكفاءة استخدام الكربون (CUE)، وزمن الاستجابة، وفقدان الحزم، وذلك عبر ظروف تحميل مختلفة. وقد أظهر النموذج التكعيبي حساسية أكبر لتقلبات الحمل، وعبّر بشكل أكثر دقة عن ديناميكيات استهلاك الطاقة في البيئات الواقعية ذات الاستخدام العالي، بينما وفّر النموذج الخطي سهولة في الحسابات وتقديرات محافظة. أدى دمج 50% من مصادر الطاقة المتجددة إلى تقليل كبير في كل من الانبعاثات والتكاليف، حيث سجّل النموذج الخطي انخفاضًا بنسبة 33.3% في انبعاثات CO_2، و71.5% في مؤشر CUE، و15.4% في التكاليف، بينما حقق النموذج التكعيبي انخفاضًا بنسبة 33.3% في انبعاثات CO_2، و23.2% في CUE، و24.6% في التكاليف التشغيلية، مما يعزز فعالية الطاقة النظيفة دون التأثير على الأداء أو جودة الخدمة.

Introduction

In consideration of the rapid advancements in information technology and the escalating dependence on digital services, data centres have evolved into a fundamental element of the global digital infrastructure [1].They establish the requisite environment for the functioning of cloud computing services, big data analytics, artificial intelligence applications, and various contemporary technologies [2]. Accompanying this substantial proliferation, environmental and economic challenges have arisen concerning energy consumption and emissions associated with the operation of these centres, thereby underscoring the imperative to enhance energy efficiency and mitigate the resultant carbon footprint [3].

Cloud computing

Cloud computing is a transformative technological advancement that enables remote access to storage, processing, and applications anytime and anywhere [4] [5].This model relies primarily on data centers that host massive global server infrastructures [5]. Since the 1990s, cloud systems evolved from local servers to large-scale platforms offered by major providers like Amazon, Google, and Microsoft [6,7]. This growth has introduced environmental concerns, particularly high energy consumption and increased carbon emissions.

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Data Centre

Data centers constitute the backbone of cloud computing architecture, providing the infrastructure for hosting computational resources and delivering services over the Internet through extensive networks of servers, storage, and communication systems [8] By centralizing computational workloads, data centers improve operational efficiency and reduce the need for localized infrastructure [9]which necessitates a balanced approach between performance and energy consumption [1]. With the rapid global expansion in the number and scale of data centers, it has become imperative to assess their resource utilization efficiency and adopt sustainability-oriented enhancement strategies [10].

Finally, networks are essential yet energy-intensive components. Devices such as switches and NICs contribute significantly to IT energy consumption [11]. Studies show that optical networking can reduce consumption by up to 23% [12], while Google's carbon-aware load management leverages network architecture to relocate workloads to lower-emission periods and regions [13].

This study focuses on core components directly linked to energy consumption and carbon emissions. Servers, which account for up to 60% of total energy use in data centers [14,15], are critical for service reliability and performance [16].

Energy Consumption and Environmental Implications of Data Centers

Data centers, as the foundation of global digital infrastructure, are experiencing rapid growth in scale and capacity. This expansion has led to significant environmental concerns, particularly high energy consumption and carbon emissions [17]. Current estimates suggest that data centers consume about 1% of global electricity, a figure expected to reach 8,000 TWh by 2030 [17]. With over 8 million active data centers globally, growing at 12% annually, projections indicate their carbon footprint could account for 5.5% of total global emissions by 2025—equivalent to 43 million tons of CO_2 [18]. Such excessive energy use not only contributes to climate change but also raises public health risks and operational costs due to emission-related policies and carbon taxes [17,18,21] Moreover, carbon performance increasingly affects an organization's sustainability reputation and alignment with global environmental standards [22].

With the substantial proliferation and advancement of data centers, a principal challenge lies in reconciling optimal performance with diminished energy utilization and carbon emissions. The majority of sanctioned energy models fail to consider the implications of elevated loads or the incorporation of renewable energy sources, underscoring the necessity for more precise models that accurately represent this evolving paradigm.

With the rapid growth of data centers, there has been increased scientific interest in studying their energy consumption and the associated environmental impact of carbon dioxide emissions. A summary of the most important related studies is presented in Table 1. Numerous studies have proposed estimation and optimization models, often incorporating renewable energy sources to reduce both operational costs and emissions. For instance, Dayarathna et al. classified 200 energy models into physical and software-based categories, introducing a four-stage methodology that included hybrid models based on linear approaches [23] Sheme et al. addressed poor renewable energy utilization by developing a smart scheduling algorithm in a CloudSim environment, achieving 75% solar power usage and a 21% improvement over traditional methods [24]. Similarly, Wu et al. proposed the PCM-ENN framework using Elman neural networks to estimate energy consumption in cloud servers, outperforming traditional methods like linear regression and Joulemeter with high accuracy (1.6% on Linux, 3.7% on Windows) [25]. In response to the high carbon footprint of data center operations, Radovanović et al. presented Google's Carbon-Aware Computing platform, which strategically places tasks based on carbon intensity, yielding 1–2% energy savings during peak emission periods [4]. More recently, Sarkar et al. developed a multi-agent reinforcement learning (MARL) system for intelligent energy and carbon management, achieving notable reductions in energy use (14.4%), emissions (14.5%), and cost (13.7%) without performance compromise [26]Additionally, Pia et al. proposed a conceptual model with 1200 servers, integrating cooling systems and simulated via CloudSim. Their approach reduced energy consumption by 14% and improved the energy efficiency index from 1.37 to 1.16, demonstrating the value of resource-aware modeling in enhancing data center sustainability [2].

Data center companies are adopting several strategies to reduce their carbon footprint and promote environmental sustainability, including relying on renewable energy sources, improving infrastructure efficiency, and using artificial intelligence technologies to manage load. Prominent examples include Google's commitment to operating carbon-neutral operations by 2030, Salesforce's goal of achieving carbon neutrality with 100% renewable energy, and Microsoft's goal of becoming carbon negative by 2030 and 100% renewable energy by 2025.[27,28]

Table 1: summarizes previous studies on energy and emissions management in data centers

Ref.	Approach / Model Type	Tool/ Environment	Main Objective	Key Findings
[23]	Analytical Survey of Power Models	200 hybrid models	Classify 200+ energy models (hardware/softw are based	Proposed 4-stage modeling framework
[24]	Smart scheduling for multi-source energy in DCs	CloudSim (100 hosts, 200 VMs, 120 kWh)	Enhance renewable energy use by balancing solar, grid, battery power	75% solar, 20% grid, 5% battery; +21% solar use vs traditional
[25]	Neural Network Modeling (PCM-ENN	CloudSuite , Sysbench	Predict server energy using temporal performance metrics	MRE: 1.6% (Linux), 3.7% (Windows
[26]	Carbon-aware task scheduling (Google)	Google Data Centers	Reschedul e tasks based on grid carbon intensity	1–2% energy reduction at peak carbon hours
[26]	Multi-Agent Reinforcem ent Learning (MARL)	Real-world deployment	Optimize energy and carbon with adaptive control	-14.4% energy, -14.5% CO_2, -13.7% cost
[17]	Simulation + AI-based resource management	Enhanced CloudSim	Reduce energy and emissions via intelligent optimization	PUE reduced from 1.37 to 1.16

Data centers are among the largest consumers of energy and significant contributors to global carbon emissions. This paper presents a comparative evaluation of two mathematical energy consumption models—the linear and cubic models—within a simulated cloud data center environment using the CloudSim toolkit. Key performance indicators were analyzed, including total energy consumption, carbon dioxide (CO_2) and carbon dioxide equivalent (CO_2e) emissions, cost, power usage effectiveness (PUE), carbon usage effectiveness (CUE), response time (latency), and packet loss, under varying workload conditions.The cubic model demonstrated greater sensitivity to workload fluctuations and more accurately captured the dynamics of energy consumption in high-utilization environments, while the linear model offered computational simplicity and conservative estimates. The integration of 50% renewable energy sources led to substantial reductions in both emissions and operational costs. Specifically, the linear model recorded a 33.3% reduction in CO_2 emissions, a 71.5% improvement in CUE, and a 15.4% decrease in cost, while the cubic model achieved a 33.3% reduction in CO_2 emissions, a 23.2% improvement in CUE, and a 24.6% decrease in operational cost—demonstrating the effectiveness of clean energy adoption without compromising system performance or service quality.

The Role of Renewable Energy in Sustainable Data Centre Operations

With the growing energy demands of data centers, the adoption of renewable energy sources has become a key strategy to enhance sustainability and reduce environmental impact [29]. Renewable energy technologies, particularly solar and/or wind, offer effective alternatives to fossil fuels by significantly lowering carbon emissions and operational costs [30-36]. Many global technology leaders, including Google, have successfully integrated these sources to power their data centers with clean, carbon-neutral electricity [26]. These efforts highlight the potential of renewables in supporting energy-efficient, environmentally responsible data center operations.

Research Methodology

This investigation employs a dual-phase simulation methodology utilizing CloudSim to assess the performance metrics and environmental consequences of two distinct power consumption models—linear and cubic—across varying load scenarios in a cloud data centers depicted in Fig. 1 and elaborated upon in Table 2, the simulated data center is comprised of 1,000 servers, each endowed with 16 CPU cores, 16 GB of RAM, and 2 TB of storage capacity, alongside a network bandwidth of 1,000 Mbps per server. The duration of the simulation was established at 24 hours, during which three workload scenarios were scrutinized: 10%, 50%, and 80% utilization, indicative of light, medium, and high processing loads, respectively [37-40]. The power parameters, such as idle power 120w and its maximum value 350W, are shown in Table 3.

Table 2: Parameters used as inputs to the simulation models

No. of Data Center	No. of Servers	No. of Cores	Memory Size (GB)	Storage Capacity (TB)	No. of Messages (MB\S)
1	1000	8	16	2	10

Operational cost: Operational cost denotes the financial expenditures associated with the functioning of a data center, predominantly encompassing the electrical energy consumption requisite for the operation of servers and ancillary components over a specified timeframe. This cost serves as a pivotal metric for assessing resource efficiency and the economic ramifications [41].

Table 3: Parameters used as inputs to the simulation models

Bandwidth (GBPS)	Carbon Factor (coal)	P_idle (Watt)	P_max (watt)
1	0.8	120	350

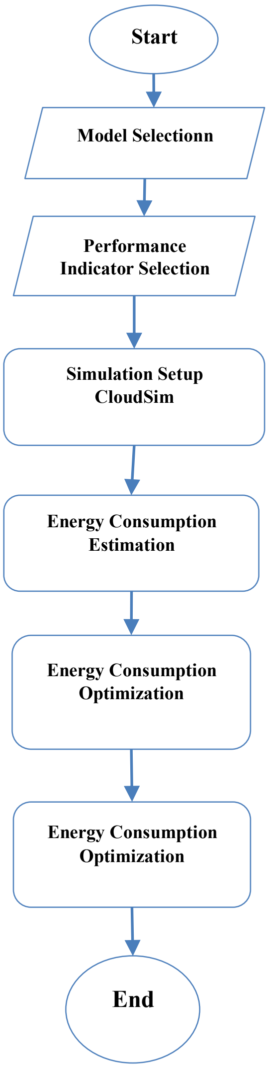

Fig. 1: Research methodology flowchart

Packet Loss: The loss rate signifies the proportion of data that is lost during the process of transmission across a communications network or within the confines of a data center environment. This metric is employed to appraise the quality of communication and the dependability of data transmission, given that a heightened loss rate adversely influences performance and operational efficacy [42,43].

Carbon Footprint Metrics in Data Centers

Carbon dioxide emissions (Q_{CO_2})

CO_2 is a primary greenhouse gas resulting from fossil fuel combustion and is widely used in carbon footprint assessments due to its strong influence on global warming [44]. It is calculated using Eqn. (1) [45]:

$$Q_{CO_2} = EC \times EF_{CO_2} \tag{1}$$

Where: Q_{CO_2}: Carbon dioxide emissions (kg/year), EC: Annual energy consumed (kWh/year), and EF_{CO_2}: Emission factor (kg CO_2/kWh). The EF_{CO_2} for several countries are presented in [46-48]

Power Usage Effectiveness (PUE)

measures the energy efficiency of data centers by comparing total facility energy to IT equipment energy; a value of 1.0 indicates ideal efficiency [27]. This metric, however, excludes workload quality and should be used alongside environmental indicators, It is calculated using Eqn. (2) [49].

$$PUE = \frac{\text{T FE}}{ITEE} \tag{2}$$

Where: PUE: Energy Usage Efficiency, TFE : Total energy consumed by the data center, ITEE: Energy consumed directly by technical devices such as servers and storage.

The Carbon footprint

quantifies the total direct and indirect greenhouse gas emissions from an activity—such as data centre operations—expressed in CO_2e, and includes energy use, transport, and infrastructure It is calculated based on energy consumption and the carbon intensity of each component [50]. It is calculated using Eqn. (3) [27]:

$$CF = \sum_{k=1}^{n} CIi * Ei \tag{3}$$

Where: Cf: Total Carbon Footprint, CIi: Carbon intensity of a resource or item i (in kg CO_2/kWh), Ei: Energy consumed by the item or source i (in kWh), n: Number of items or sources consuming energy.

While various greenhouse gases are encompassed within the assessment of the carbon footprint, this investigation predominantly emphasizes carbon dioxide (CO_2) emissions, owing to their preeminent impact on overall emissions derived from energy consumption and their significant correlation with electricity utilization in data centers.

Carbon Utilization Effectiveness (CUE)

measures the ratio of carbon emissions (CO_2) to IT energy consumption, offering insight into the environmental efficiency of IT operations It is calculated by dividing total CO_2 emissions by the energy consumed by IT equipment [51]. It is calculated using Eqn. (4) [27]:

$$CUE = \frac{TCO_2\ E}{\text{ITEC}} \tag{4}$$

Where: CUE: Carbon utilization efficiency, $TCO_2\ E$: Total carbon dioxide (kg), ITEC : Annual Information Technology Energy consumption in information technology equipment (kWh).

Power Consumption Models

Energy consumption models are essential tools for analyzing and enhancing the efficiency of data center infrastructure. These models aim to accurately represent the relationship between resource utilization and energy consumption rates. In this context, the study focuses on utilizing selected models integrated within the CloudSim simulation platform to evaluate the impact of energy management strategies on system efficiency in terms of both performance and power consumption

Linear Model

The linear power model posits a direct correlation between CPU utilization and energy consumption, which escalates in a proportional manner relative to the workload, as represented by Eqn. (5). This model is employed due to its straightforwardness and efficacy in simulating systems operating under stable or moderate load conditions [52].

$$P(u) = P_{idle} + (P_{max} - P_{idle}).u \tag{5}$$

Where: $P(u)$: Power consumed at a utilization level u, P_{idle}: Power consumption at idle state, P_{max}: Maximum power consumption at full utilization, u: CPU utilization ratio (ranging from 0 to 1).

Cubic Model

The cubic power model is predicated on a nonlinear correlation between CPU utilization and energy consumption, wherein power utilization escalates more precipitously at elevated loads, as delineated by Eqn. (6) [52]. This model is favored due to its superior precision in depicting authentic energy dynamics under fluctuating and demanding workloads.

$$P(u) = P_{idle} + (P_{max} - P_{idle}).u^3 \tag{6}$$

Where: $P(u)$: Power consumed at a utilization level u, P_{idle}: Power consumption at idle state, P_{max}: Maximum power consumption at full utilization, u^3 Cube utilization ratio (meaning that the increase in energy consumption becomes more severe the closer the load gets to 100%) The importance:

Two stages were performed in this study:

Estimation Phase: Power Consumption and CO_2 Emissions under Conventional Grid Energy.

All energy is procured from the traditional electrical grid, presuming 0% contribution from renewable energy sources. The carbon emission factor is established at 0.8 kg CO_2/kWh, which is within the range reported by the International Energy Agency (IEA) in its "CO_2 Emissions in 2022" report. According to this report, countries heavily reliant on fossil fuels, such as coal and natural gas, can exhibit carbon intensities ranging between 0.7 to 1.0 kg CO_2/kWh, indicating a highly carbon-intensive energy profile [53].

Optimization Phase: Power Consumption and CO_2 Emissions under 50% Renewable Energy Integration.

An integration of 50% renewable energy (as it announced in the Libyan energy strategy for the years 2025-2050 [54,55]) has been assumed in this optimization scenario, comprising approximately 35% solar and 15% wind energy. This configuration reflects a forward-looking energy mix inspired by the increasing global deployment of clean energy, Although the global average shares of solar and wind were 5.5% and 11.2% respectively in 2023, this simulation envisions a more ambitious integration in alignment with future sustainable data center practices.

The energy produced by a specific PV solar module can be estimated by [56,57]:

$$P_{PV} = P_{STC}\left[1 + \beta_p (T_{cell} - T_{STC})\right] \frac{H_t}{H_{STC}} \tag{7}$$

Where: T_{STC} and T_{cell} are the celll's surface temperature at Standard Test Condition, β_p is the power temperature coefficient. The challenge that researchers will face is to find an empirical equation to determine the cell surface temperature T_{cell} [58]:

$$T_{cell} = T_{\infty} + 7.8 \times 10^{-2} H_t \tag{8}$$

The energy produced by a specific wind turbine can be estimated by [59,60]:

$$P_w = \begin{cases} P_{rat} & \leq u_t < u_{cut-off} \\ P_{rat}\left(\dfrac{u_t - u_{cut-in}}{u_{rat} - u_{cut-in}}\right) & u_{cut-in} < u_t < u_{rat} \\ 0 \quad u_t \leq u_{cut-in} & OR \quad u_t \geq u_{cut-off} \end{cases} \tag{9}$$

Where P_{rat} is the rated power of the wind turbine in kW; u_{cut-in} , u_{rat} and $u_{cut-off}$ are the cull-in, rated and cut-off wind speed in m/s, and u_t is the wind speed at the hub height

(h_t) in m/s. Since the wind speeds (u_0) provided by meteorological stations or climate data platforms measured at a height (h_0) different from the wind turbine hub height (usually at 10 meters), it is essential to extrapolate them at the turbine's hub height. In this study, the exponential law was adopted based on recommendations from local researchers [59]. Therefore, the wind speed at the height of the wind turbine tower is calculated using the following equation [59]:

$$u_t = u_0 \left(\frac{h_t}{h_0}\right)^{\propto} \tag{11}$$

where, α is the wind shear coefficient which is dependent on the atmospheric stability and the location terrains [59]. In this work α=1/7 [59].

The electrical characteristics of some types of PV solar modules are presented in [61, 62] and for some wind turbines are described in [63,64]

Assumptions, Limitations, and Uncertainties

Lack of access to a real data centre for primary data collection

It was assumed that operational parameters, workload profiles, and hardware specifications could be accurately obtained from peer-reviewed studies, technical reports, and prior research. This assumption was necessary due to the unavailability of direct access to an operational data centre. While such secondary sources are widely accepted in simulation-based research, they may not fully capture the specific variations and operational patterns of an actual facility.

Exclusion of cooling systems in the simulation

The study assumed that the absence of cooling-related energy consumption modelling would not significantly alter the comparative performance evaluation of the tested power models. This exclusion was based on the fact that CloudSim does not natively support cooling system modelling [65]. However, in real-world scenarios, cooling systems can account for up to 40% of total energy use, meaning their omission limits the direct applicability of results to complete data centre operations.[66]

Absence of a physical testing environment

It was assumed, in line with prior simulation-based research, that CloudSim could yield sufficiently accurate comparative insights into the performance of different mathematical power models. While simulations enable controlled and repeatable parameter variation, they inherently fail to reproduce the full complexity, inefficiencies, and stochastic behaviours of an operational data centre [67].

Limitations and Real-World Relevance

These assumptions collectively introduce limitations to the study's findings. The lack of real-world measurements and the exclusion of cooling systems constrain the precision of absolute energy and emissions values. Nevertheless, the comparative nature of the analysis—evaluating models under identical simulated conditions—ensures that relative performance trends remain valid and informative. In practice, further validation in an operational data centre would be required to confirm the applicability of these findings, particularly in environments where cooling and auxiliary systems play a significant role in total energy consumption.

The main source of uncertainty in the current research is the information provided by the database, for example, there is a significant difference in the EF_{CO_2} for Libyan power generation sector, reaching up to 30%, which increases the uncertainty in the results and negatively impacts on decision-making [68].

Results and Discussion

The findings elucidate the assessment and enhancement stages subsequent to the simulation procedure for the two models (linear and cubic), emphasizing environmental, energy, and performance metrics. The findings demonstrate the ramifications of incorporating renewable energy sources across various operational conditions. The tables present the evaluations of data center components alongside carbon dioxide metrics, which are considered a significant factor following the improvement phase.

Energy Consumption Estimation stage

Linear Power Model

The aggregate power demonstrated a pronounced linear relationship with both the levels of resource utilization and the quantity of servers, with total consumption rising dramatically from 211,100 to 1,338,800 kW. Servers represented the primary source of power consumption, whereas network and memory utilization were solely determined by bandwidth and memory capacity. Carbon dioxide emissions exhibited a direct relationship with overall energy consumption, where the Carbon Usage Effectiveness (CUE) was consistently observed at 3.68, and the Power Usage Effectiveness (PUE) remained approximately at 1.0. As illustrated in Fig. 2, operational expenditures escalated in direct proportion to the workload and the number of servers, with negligible influence from memory and bandwidth parameters, as substantiated in Table 4.

Table 4: The linear model at the estimation stage

Component	Utilization (10%)	Utilization (50%)	Utilization (80%)
Servers (kW)	210000	850000	1330000
Network (kW)	1000	5000	8000
Memory (kW)	80	400	640
Total power (kW)	211100	855500	1338800
CO2 (kg)	94572.80	383264	599782.40
COST ($)	25332	102660	160656
PUE		1	
CUE		3.68	
Latency (ms)	95	75	60
Packet Loss Probability	0.001	0.025	0.064

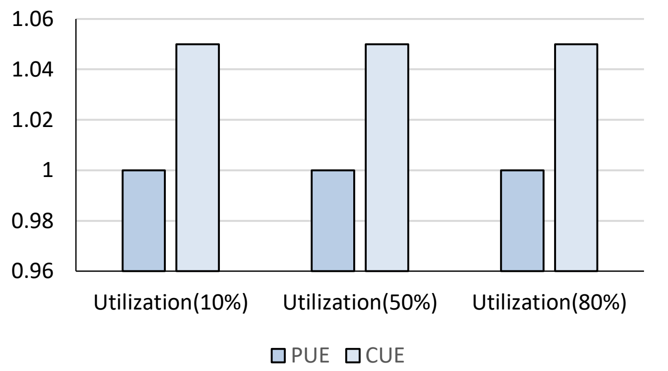

Fig. 2: Key outputs of performance indicators (PUE, CUE) using the linear model at the estimation stage

Cubic Power Model

The cubic model exhibited an augmented degree of energy consumption concomitant with an increased rate of CPU utilization, thereby underscoring its non-linear attributes. Servers emerged as the predominant source of power consumption, while both carbon dioxide emissions and carbon footprint escalated in correlation with the quantity of servers and processing cores. The Power Usage Effectiveness (PUE) metric exhibited stability at 1.09, whereas the Carbon Usage Effectiveness (CUE) experienced a decline to 2.33, signifying enhanced environmental efficiency under fluctuating load circumstances. As illustrated in Fig. 3, operational expenditures escalated in tandem with server load, with minimal impact attributable to memory or bandwidth consumption. Furthermore, a decrease in latency was noted as the load intensified, while packet loss increased due to network congestion, as evidenced in Table 5.

Table 5: The cubic model at the estimation stage.

Component	Utilization (10%)	Utilization (50%)	Utilization (80%)
Servers (kW)	50200	75000	152400
Network (kW)	500	2500	4000
Memory (kW)	15.18	169.71	343.46
Total power (kW)	60864.29	93271.53	188229.54
CO_2 (kg)	25319.54	38800.96	78303.49
COST ($)	8052	54660	129936
PUE		1.09	
CUE		2.33	
Latency (ms)	96.9	82.5	69.6
Packet Loss Probability	0.0012	0.3	0.0768

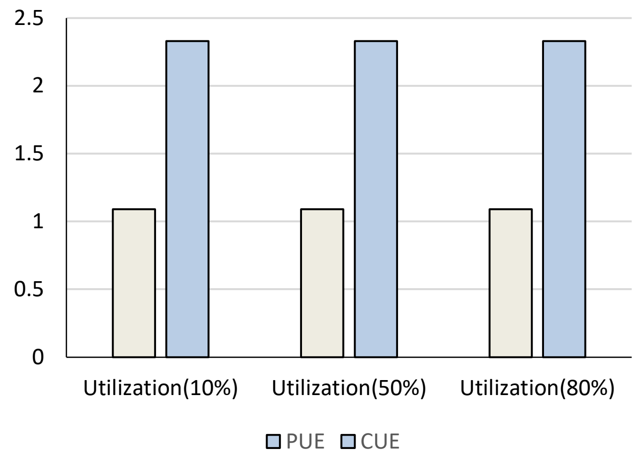

Fig. 3: Key outputs of performance indicators (PUE, CUE) using the cubic model at the estimation stage

Energy optimization Estimation stage

Linear Power Model

Incorporating 50% renewable energy into the PowerModelLinear framework significantly improved environmental and economic efficiency. CO_2 emissions were reduced by 33.3%, and the equivalent ratio was significantly reduced by 33.4% thanks to the adoption of a cleaner energy mix, while operating expenses were significantly reduced across all usage levels. The improvement rate reached 15.42%, and the power usage effectiveness (PUE) stabilized at 1.0, indicating optimal energy utilization. The carbon usage effectiveness (CUE) also improved significantly, decreasing from 3.68 to 1.05. This was achieved by 71.4% Additionally, network performance metrics, such as latency and packet loss, remained within acceptable limits, confirming the maintenance of quality of service. Table (6) summarizes these results.

Cubic Power Model

The integration of 50% renewable energy into the Cubic Power Model yielded clear environmental benefits, with carbon dioxide (CO_2) emissions reduced to 60,233.45 kg, reflecting an improvement rate of 33.3%. Meanwhile, carbon dioxide equivalent (CO_2e) emissions decreased to 374,652.07 kg, reaching a reduction rate of 23.08%, indicating a significant enhancement in environmental performance. Operating expenses recorded substantial decreases across all utilization levels, attributed to the lower cost of electricity generated from renewable sources, with an overall improvement of 24.6%. The Power Usage Effectiveness(PUE) remained stable at 1.09, while the Carbon Usage Effectiveness (CUE) improved from 2.33 to 1.79, representing a reduction of 23.10%. Despite the nonlinear increase in total energy consumption with higher utilization, servers remained the primary contributors to energy usage. Network performance indicators, such as latency and packet loss, stayed within optimal operational thresholds, reflecting the system's continued stability and efficiency. These results are presented in Table 7.

Table 6: The linear model in the optimization phase when 50% renewable energy is incorporated.

Component	Utilization (10%)	Utilization (50%)	Utilization (80%)
Servers (kW)	210000	850000	1330000
Network (kW)	1000	5000	8000
Memory (kW)	80	400	640
Total power (kW)	211100	855500	1338800
CO_2 (kg)	27020.80	109504	171366.40
COST($)	21426.65	86833.25	135888.20
PUE		1	
CUE		1.05	
Latency (ms)	95	75	60
Packet Loss Probability	0.001	0.025	0.064

Table 7: The cubic model in the optimization phase when 50% renewable energy is incorporated.

Component	Utilization (10%)	Utilization (50%)	Utilization (80%)
Servers (kW)	50200	75000	152400
Network (kW)	500	2500	4000
Memory (kW)	15.18	169.71	343.46
Total power (kW)	60864.29	93271.53	188229.54
CO_2 (kg)	19476.57	29846.89	60233.45
COST ($)	6177.73	9467.06	19105.30
PUE		1.09	
CUE		1. 79	
Latency (ms)	96.9	82.5	69.6
Packet Loss Probability	0.0012	0.3	0.0768

The fixed power usage efficiency (PUE) values and fixed consumption patterns of critical components, such as servers, memory, and the network, reflect the role of renewable energy. Renewable energy serves only as an alternative source of electricity generation; it does not affect infrastructure design, operation, or energy demand. Thus, while the energy source becomes cleaner and more cost-effective, the actual energy use by system components remains unchanged. Therefore, noticeable improvements are limited to environmental and financial aspects, without impacting technical performance or utilization levels.

In order to substantiate this assertion, Table 8 delineates a comparative analysis between the present investigation and a contemporary related inquiry [26], emphasizing congruities and divergences in aims, methodologies, and results.

Conclusions

The choice of a data centers energy consumption model should be aligned with its workload characteristics and sustainability goals. While the linear model is simple, easy to compute, and produces conservative estimates, it has limitations in high-load environments and can lead to overestimation of carbon emissions. In contrast, the cubic model demonstrates more accurate performance and lower emissions and costs, especially when renewable energy sources are integrated into the infrastructure. Therefore, the cubic model is recommended as an effective and comprehensive reference framework for modeling energy consumption in green data centers seeking to improve environmental efficiency and reduce their carbon footprint. Due to its better ability to represent the nonlinear relationship between load and energy consumption, it achieves more accurate estimates, especially at high loads, and contributes to reduced emissions and operational costs.

Table 8: Comparison between the current study and previous studies

Ref.	Approach Model Type	Tools	Main Objectives	Key findings
[26]	Multi-Agent Reinforcement Learning (MARL)	Real-world deployment	Optimize energy and carbon with adaptive control	-14.4% energy, -14.5% CO_2, -13.7% cost
E.M.Ali (2025)	Simulation using Linear, Cubic models	CloudSim	Estimate optimize energy, emissions & cost with 50% renewable energy	The cubic model is the best, reducing CO2 emissions by 33.3%, costs by 24.6%, and energy consumption by 23%, without compromising performance.

Recommendations for Future work

Future directions should focus on expanding energy models to incorporate additional subsystems such as cooling, which represents a major energy consumer in data centers. Moreover, the integration of hybrid or AI-based modeling approaches can enhance adaptive optimization capabilities. Simultaneously, improving software design and algorithm efficiency can reduce redundant server operations, leading to lower energy usage and emissions. Operational strategies such as virtual machine consolidation and dynamic load balancing, coupled with customized carbon mitigation techniques, are essential to ensure a balanced approach between performance and sustainability.

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