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Systematic Review

A Systematic Review of Energy Efficiency Metrics for Optimizing Cloud Data Center Operations and Management

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Abstract: Cloud Data Centers (CDCs) are an essential component of the infrastructure for powering the digital life of modern society, hosting and processing vast amounts of data and enabling services such as streaming, Artificial Intelligence (AI), and global connectivity. Given this importance, their energy efficiency is a top priority, as they consume significant amounts of electricity, contributing to operational costs and environmental impact. Efficient CDCs reduce energy waste, lower carbon footprints, and support sustainable growth in digital services. Consequently, energy efficiency metrics are used to measure how effectively a CDC utilizes energy for computing versus cooling and other overheads. These metrics are essential because they guide operators in optimizing resource use, reducing costs, and meeting regulatory and environmental goals. To this end, this paper reviews more than 25 energy efficiency metrics and more than 250 literature references to CDCs, different energy-consuming components, and configuration setups. Then, some real-world case studies of corporations that use these metrics are presented. Thereby, the challenges and limitations are investigated for each metric, and associated future research directions are provided. Prioritizing energy efficiency in CDCs, guided by these energy efficiency metrics, is essential for minimizing environmental impact, reducing costs, and ensuring sustainable scalability for the digital economy.

Keywords: cloud data centers; energy efficiency; energy efficiency metrics; power supply

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1. Introduction

1.1. Background and Statistics

In recent years, the exponential growth of data-driven services—enabled by cloud computing and supported by hyper-scale infrastructure—has positioned CDCs as an essential component within global information and communication networks. Their central role in powering Artificial Intelligence (AI), big data analytics [1–6], e-commerce [7], streaming platforms [8–13], and edge computing [14–18] has made them critical to the digital infrastructure across all economic sectors. However, this massive computational footprint comes at a significant energy and environmental cost. While CDCs have become central to digital services, their growing computational load has made them one of the most energy-intensive classes of the digital infrastructure [19].

Global energy consumption by CDCs is projected to rise from 200 TWh in 2016 to nearly 2967 TWh by 2030, accounting for a significant share of total electricity use [20]. In the United States, CDCs consumed approximately 4.4% of total electricity in 2023, with projections reaching between 6.7% and 12% by 2028, mainly due to rising AI workloads [21]. Worldwide, electricity demand from CDCs is expected to exceed 857 TWh by

2028, with a Compound Annual Growth Rate (CAGR) of 19.5%, outpacing several major industrial sectors [22]. Within these facilities, Information Technology (IT) equipment accounts for roughly 60% of electricity consumption, while cooling and power delivery systems contribute another 30–40% [23]. This level of consumption places substantial pressure on energy infrastructure and raises critical concerns regarding sustainability, grid stability, and long-term cost efficiency [24].

These issues are further amplified by instabilities in the global energy market. Electricity prices are becoming increasingly volatile, influenced by geopolitical conflict, supply chain constraints, and fuel price fluctuations [25]. Meanwhile, many regions face escalating grid stress as electricity demand from both hyper-scale CDCs and electrified transport grows. Reports from the International Energy Agency (IEA) and the World Bank have noted the growing mismatch between CDC growth and the modernization rate of electric grids, particularly in regions where energy security is already constrained [26,27]. As a result, CDC operators must now address not only internal energy efficiency but also the broader challenge of navigating uncertain and competitive energy markets.

In many high-growth regions, energy management and reliability have become a key constraint [28] in which CDC expansion is not an exception. In Texas, concerns over grid capacity for AI and crypto workloads were publicly raised by industry leaders [29], and Taiwan has temporarily halted the development of large CDCs due to power concerns [30]. These developments reflect a shift toward proactive energy procurement strategies. For example, Microsoft's long-term Power Purchase Agreement (PPA) with the Three Mile Island nuclear facility exemplifies efforts by major cloud providers to secure a reliable, dedicated energy supply for their infrastructure [31]. Sustainability objectives also influence the way CDCs are planned and managed. Many operators have committed to CO_2-neutral targets and 100% Renewable Energy Sources (RESs). As of 2023, over 120 digital realty facilities operate on Renewable Energy Sources (RESs), supported by regional PPAs and clean energy procurement strategies [32]. In addition, thermal re-use systems, such as district heating with server exhaust and aquifer thermal storage, as well as water-efficient cooling technologies, are being deployed to reduce environmental impact [33]. These initiatives signal a broader shift from traditional energy efficiency metrics to integrated sustainability and resilience planning.

Existing metrics such as Power Usage Effectiveness (PUE), Data Center Infrastructure Efficiency (DCiE), and Carbon Usage Effectiveness (CUE) have been widely adopted to evaluate CDC energy performance [34,35]. However, these metrics often provide only a partial view, as they typically exclude software-related inefficiencies, dynamic workloads, and grid-level CO_2 intensity. With the increasing adoption of virtualization, containerization, and serverless computing, these limitations are becoming more significant. As a result, new metrics—such as Server Power Usage Effectiveness (SPUE)—have been proposed to address energy use at more granular levels [36]. While promising, these approaches remain under development, and their practical implementation faces challenges, in terms of standardization and integration. Therefore, a comprehensive review of energy efficiency metrics is necessary to assess their relevance, gaps, and applicability in modern CDC environments.

1.2. Systematic Review Methodology

The Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) systematic review process is a structured framework designed to ensure transparency, rigor, and reproducibility in systematic reviews [37], and our PRISMA checklist can be found in Supplementary Materials. It involves several key stages of keywords, identification, screening, eligibility, and inclusion, each important to synthesizing evidence from rele-

vant studies. The Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) framework of this review is illustrated in Figure 1:

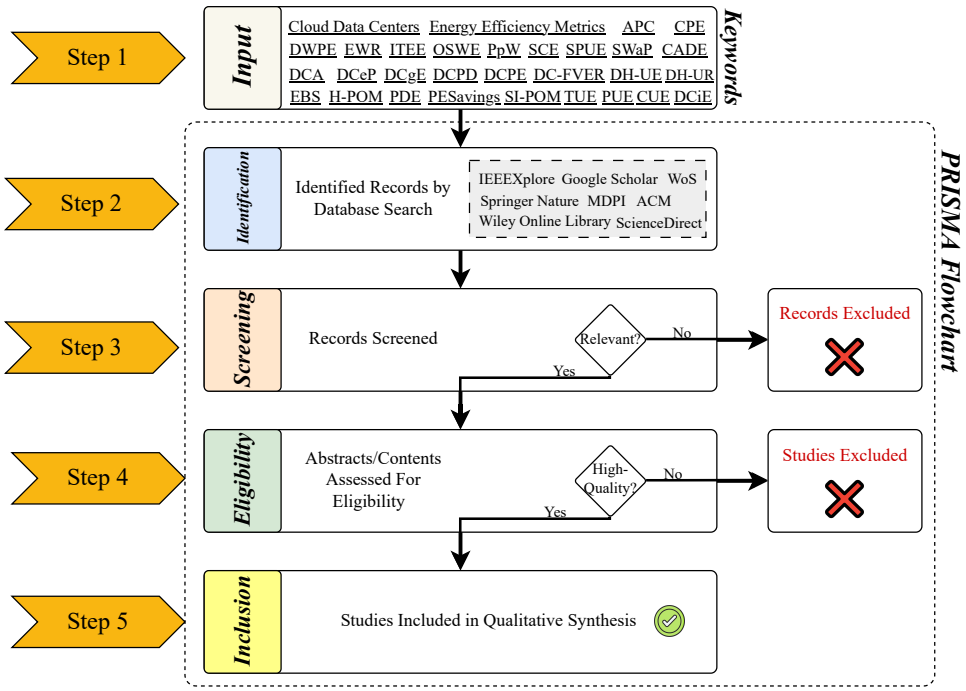


Figure 1. The Preferred Reporting Items for Systemic reviews and Meta-Analyses (PRISMA) process of this systematic review, including keywords, identification, screening, eligibility, and inclusion.

The process begins with keywords. Firstly, a group of keywords is selected to make a comprehensive search strategy, centered on carefully chosen keywords. These keywords are derived from the research question, which results in the energy efficiency of CDCs, the metrics, and their definition.

Then, the identification phase starts, involving the search strategy execution across multiple databases, such as *IEEEXplore, Google Scholar, Web of Science (WoS), Springer Nature, MDPI, ACM, Wiley Online Library*, and *ScienceDirect*, to locate potentially relevant studies. Additional sources, such as conference proceedings, should also be searched. The goal is to cast a wide net, retrieving all records that might address the research question.

As the third step, during the screening phase, the deduplicated records are evaluated against predefined inclusion and exclusion criteria, typically in two stages: title/abstract screening and full-text review. In the first stage, the reviewers assess titles and abstracts to determine whether the studies are potentially relevant, excluding those that do not meet the criteria. The eligibility phase (Step 4) involves a detailed assessment of the full texts of the studies that passed the screening phase. Finally, the inclusion phase (Step 5) results in the selection of studies that fully meet the eligibility criteria and are included in the systematic review.

1.3. Literature Review

In the past ten years, the overall interest in the energy efficiency of CDCs has been evident, based on the publications published in Scopus (Figure 2) and their publication types (Figure 3). Based on these statistics, the journal publication type had the most significant share of research presentations on the energy efficiency metrics of CDCs (especially in 2024).

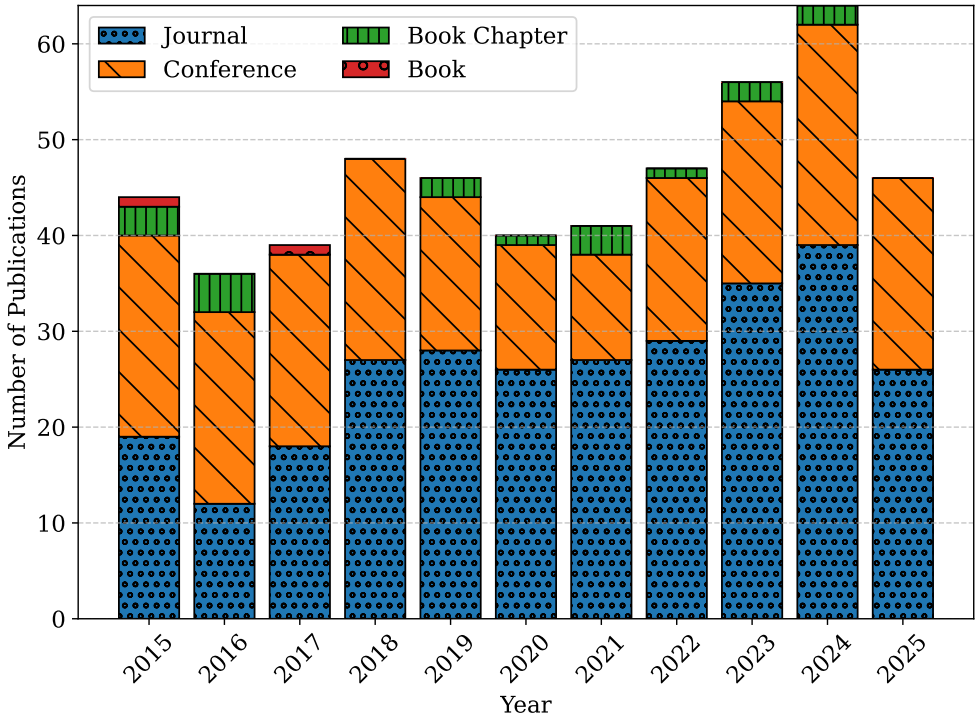


Figure 2. Overview of related Scopus publications on *energy efficiency of CDCs*.

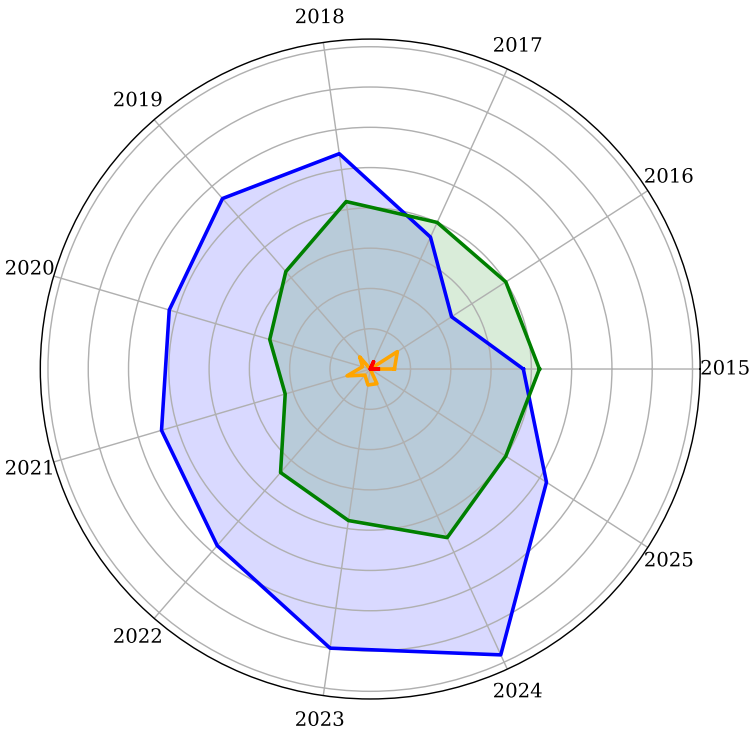


Figure 3. Overall statistics of Scopus publication types on *energy efficiency of CDCs* (***Journal Papers***, ***Conference Papers***, ***Book Chapters***, *and* ***Books***).

A study conducted in [38] used focus groups and interviews with CDCs managers to identify split incentives, imperfect information, and reliability trade-offs as barriers to energy efficiency investments. While market failures had limited impact, the high costs of context-specific information and opportunity costs from competing priorities were more significant in slowing adoption. In another study, a two-phase research was conducted

by [39], investigating the non-technical barriers to energy efficiency. In Phase I, it was found that there were abundant technical solutions but insufficient focus on cultural shifts. Phase II's interview with 16 CDC experts presented vendor-driven procurement, facility-specific energy metrics, and design convergence due to high-density infrastructure.

A comprehensive review analyzed over 200 CDC power models, organizing them into a hierarchical framework with hardware-centric and software-centric branches [40]. The hardware-centric models spanned digital circuit, component, server, data center, and systems-of-systems levels, while the software-centric models focused on operating systems, virtual machines, and applications. Efforts to establish energy efficiency metrics for wireless networks, such as radiated base station power normalized to area and traffic load (e.g., Watts/Erlang/km² or Watts/(bits/sec)/km²), reflect industry goals to create green networks. However, a study by [41] argued that these metrics are unsuitable for wireless systems, as they conflict with effective system operation and mislead network design. On the other hand, a study by [42] enhanced energy monitoring in telecommunication central offices by introducing novel metrics alongside the heating degree days parameter: the parameter of central utilization, index of cluster reliability, and reliability index.

The energy intensity metric—the ratio of energy consumed to data volume—is used to assess energy efficiency in communication networks and CDCs. This metric was criticized in [43] for its application, noting that weak correlations between data and energy use at short time scales lead to misleading results. Additionally, the importance of energy savings in CDCs was considered by [44], who proposed a model for measuring CDCs' components to organize metrics and enhance corporate communication. The strengths and weaknesses of standard metrics were evaluated. The Power Usage Effectiveness (PUE) metric is one of the most used energy efficiency factors. The analysis conducted in [45] critiqued this metric's limitations, noting that its instantaneous measurement of electrical energy use encouraged reporting of minimum values, thus reflecting only the lowest possible energy consumption.

As another metric class, cooling and thermal management of CDCs has come under focus. Several works, such as [46–50], have evaluated and reviewed several cooling and thermal strategies, as well as metrics in CDCs. Moreover, several reviews [51–53] have also been conducted on generally investigating the energy efficiency metrics of CDCs. Therefore, by highlighting efficiency trends and recalibrating estimates, ref. [54] presented policymakers and analysts with a refined perspective on data center energy use, its drivers, and near-term efficiency potential.

Three adaptive models—of Gradient Descent-Based Regression (GDR), Maximize Correlation Percentage (MCP), and Bandwidth-Aware Selection Policy (BW)—were designed in [55] to reduce energy consumption and Service Level Agreement (SLA) violations in CDCs. These models use energy-aware techniques for detecting overloaded hosts and selecting Virtual Machines (VMs) for migration. As another alternative, the work by [56] presented the enhanced multi-objective optimization algorithm for task scheduling, combining deep reinforcement learning and enhanced electric fish optimization for energy-efficient task scheduling. Following the importance of this subject, a resource prediction-based VM allocation method was introduced by [57] that reduced energy consumption and enhanced system reliability. It optimized feed-forward Neural Networks (NNs) using a self-adaptive differential evolution algorithm incorporating multi-dimensional learning and global exploration for superior global solution searching compared to traditional gradient descent.

The same subject was applied to vehicular edge cloud computing systems in [58]. It introduced a load-balancing algorithm that redistributes vehicles across roadside units based on load, computational capacity, and data rate. A robust security mechanism integrates

an advanced encryption standard with electrocardiogram signals as encryption keys to secure data transmission. A caching strategy enables edge servers to store completed tasks, reducing latency and energy use. An optimization model minimized energy consumption while meeting latency constraints during computation offloading.

Moreover, the paper by [59] highlighted four key areas to enhance energy efficiency in CDCs: aligning architecture with emerging workloads, provisioning resources for future demands, improving the energy proportionality of machines, enhancing vertical integration across software stacks, and standardizing hardware–software interfaces for technology integration. Consequently, on the energy-management side, a hybrid policy-based reinforcement learning approach was presented in [60] for adaptive energy management in island group energy systems with constrained energy transmission. The paper introduced an island energy hub model enabling cascade energy utilization to meet island-specific demands and ensure a reliable supply. An energy management model for island groups was developed, accounting for the mismatch between energy demand and resources, in addition to the limited transmission capacity. Given the complexity of modeling, due to high renewable penetration and variable loads, the problem was framed as a model-free reinforcement learning task.

Therefore, a multi-energy trading market model based on price matching was proposed by [61] to promote collaboration across energy types and improve utilization through user participation. The model supports personalized energy responses while preserving user privacy and autonomy. A joint trading mechanism was developed to handle various energy types and time scales, reducing failures from overlooked transmission processes. Conversion devices are used to boost matching efficiency, and an income mechanism prevents operator bias. An enhanced hierarchical reinforcement learning algorithm is applied to manage large state-action spaces and sparse rewards. Furthermore, the review by [62] overviewed the trends in improving energy efficiency across cloud infrastructure, including servers, networking, management systems, and user software. It highlighted solutions, their benefits, and their trade-offs.

1.4. Existing Gaps and Contribution

In this context, the development of a unified, comprehensive understanding of energy efficiency metrics is critically needed. The current landscape includes a diverse and often fragmented set of methods, each targeting different aspects of energy performance—yet no systematic framework exists to guide their selection or application in line with evolving infrastructure models. As energy consumption continues to rise and sustainability becomes a primary design constraint, the ability to assess and manage CDC efficiency through appropriate metrics is no longer optional—it is foundational to both engineering practice and decision making.

To this end, this work overviews the energy efficiency metrics of CDCs, classifies them into two groups of IT-related and non-IT-related metrics, and investigates them in detail. Next, challenges and limitations are identified, and potential future research directions are presented. Consequently, the contributions of this work are highlighted as follows:

1. The complete analytics of the energy efficiency metrics of CDCs;
2. Presenting the energy-consuming components of a CDC;
3. Describing different centralized and decentralized setups of Uninterruptible Power Supplies (UPSs) and Power Distribution Units (PDUs) in CDCs;
4. Providing the challenges, limitations, and the associated potential research directions for each metric.

1.5. Paper Structure

The paper is structured as follows: Cloud Data Centers energy management concepts and their energy efficiency metrics are presented in Sections 2 and 3. Next, real-world case studies, challenges, limitations, and future work, as well as the conclusion, are provided in Sections 4–6, respectively.

2. Energy Management in Cloud Data Centers

Cloud Data Centers consume energy primarily for server operation, cooling systems, networking equipment, and power distribution [40,63–66]. Consequently, effective energy management in CDCs holds considerable importance. A typical CDC energy supply and consuming components are shown in Figure 4:

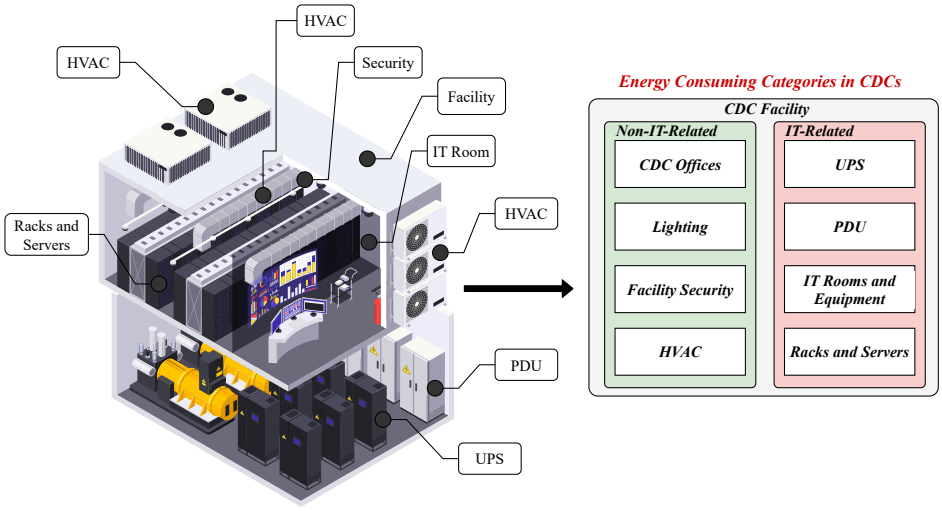


Figure 4. A typical CDC facility, with its energy supply (PDU and Uninterruptible Power Supply (UPS)), and energy consumption components (Heating, Ventilation, and Air Conditioning (HVAC), security, IT, servers, racks, etc.).

2.1. Servers and Racks

Racks and servers are the central computational engines of a CDC [67]. A server rack typically contains multiple servers stacked in vertical slots, including Central Processing Units (CPUs) [68,69], Graphical Processing Units (GPUs) [70–73], Random Accessible Memory (RAM) [74–76], storage drives [77–80], and networking interfaces [81–86]. These servers handle user requests, run applications, manage databases, and execute processing tasks. Their power draw is constant and scales with computing intensity. A high-density server environment leads to significant heat output, necessitating robust cooling solutions. Moreover, the performance-optimized design of modern servers often prioritizes speed over energy efficiency, further escalating their power needs. Thus, energy consumed by racks and servers is one of the most substantial factors in CDC energy efficiency.

2.2. Uninterruptible Power Supply (UPS)

Uninterruptible Power Supply is a system that ensures uninterrupted operation during a power failure [87,88]. It provides short-term backup power, using batteries (usually Lithium-Ion Batteries (LIBs) [89,90]), and it conditions the incoming power to protect equipment from surges, drops, and noise. These systems involve energy losses in the process of converting Alternating Current (AC) to Direct Current (DC) (to charge batteries) and DC back to AC (to power the load), known as double conversion [91–94]. These conversions are essential for high reliability; however, they

consume additional power. Moreover, batteries require ongoing charging, and in large-scale CDCs the number of UPS units is significant enough to be taken into account, making them one of the largest IT-related energy consumers.

2.3. Power Distribution Unit (PDU)

Power Distribution Units are the important component within CDCs, distributing power from the UPS or main supply to individual equipment, such as servers and network devices [95–97]. They often include transformers, circuit breakers, and monitoring features. Power Distribution Units step down voltage and convert power to appropriate formats, during which energy losses occur. Intelligent PDUs allow for real-time power consumption monitoring and environmental condition tracking, which adds to their power usage. Generally, CDCs' power supply, including UPSs, PDUs, and Renewable Energy Sources (RESs), is conducted in two forms of [98]:

1. Centralized (Figure 5): Electricity from a single UPS is distributed to multiple PDUs, which then channel the power to server racks. To avoid any delay in switching to UPS power, CDCs are equipped with double conversion UPS systems.
2. Distributed (Figures 6 and 7): Instead of a centralized UPS, a battery cabinet serves every multiple rack, supporting the servers (Figure 6). This approach eliminates double conversion by modifying server power supply units to accept both AC power from the grid and DC power from the battery cabinet. The battery cabinet distributes DC power directly to the servers. As another form of distributed UPS, a battery is integrated into each server following the UPS. This configuration eliminates the AC/DC/AC double conversion, enhancing energy efficiency during normal operation, and it positions AC distribution closer to the IT load before conversion (Figure 7).

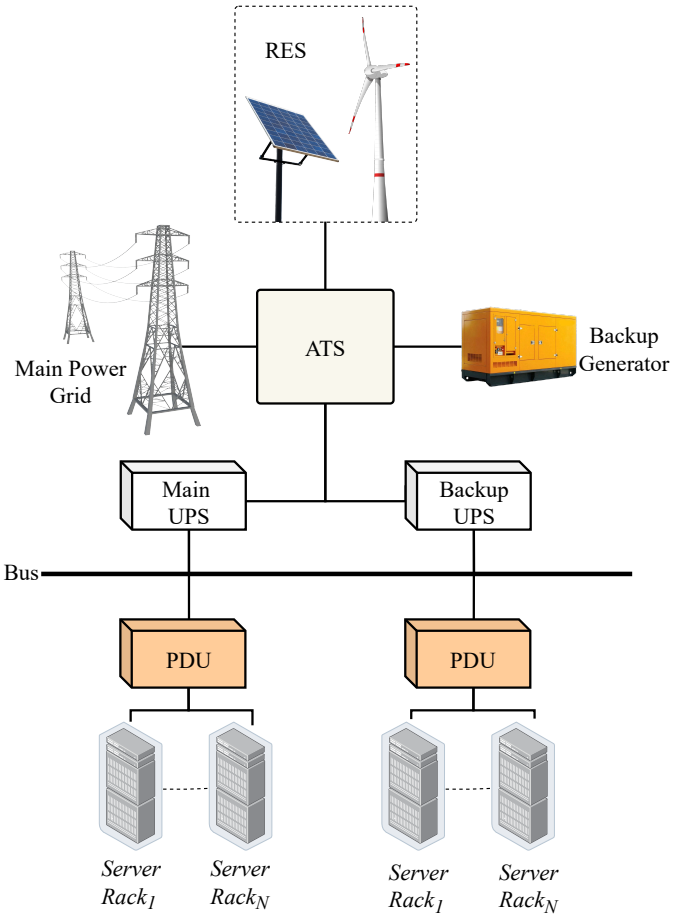


Figure 5. Centralized UPS configuration.

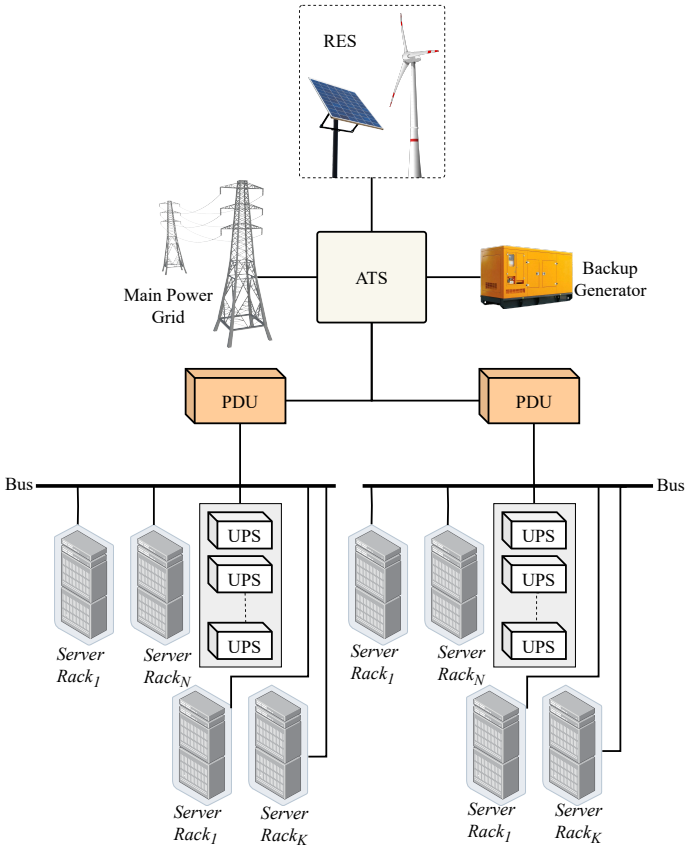


Figure 6. Decentralized UPS configuration—Type 1.

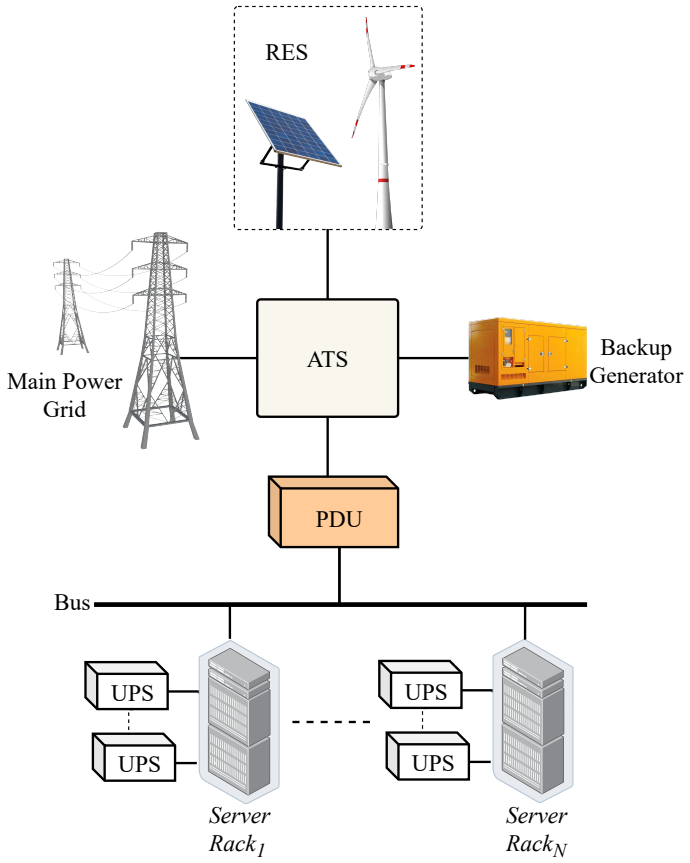


Figure 7. Decentralized UPS configuration—Type 2. The base concept for Figures 5–7 are gathered from [98], and the concept of RES is added to them.

2.4. Information Technology (IT) Rooms and Equipment

Information Technology rooms contain not only servers but also the essential components of firewalls [99], switches [100], routers [101,102], load balancers [103], storage systems, and monitoring consoles [104], which handle data routing, traffic control [105–107], storage functions, and system diagnostics. These systems run continuously and rely on redundant setups for high availability. Additionally, control rooms with operator workstations, large display walls, and supporting electronics are included in this category. Although each piece of equipment consumes less power than servers, their combined energy demand significantly contributes to the IT-related energy footprint.

2.5. Heating, Ventilation, and Air Conditioning (HVAC)

Heating, Ventilation, and Air Conditioning systems are the largest non-IT energy consumer. They are responsible for maintaining stable temperature and humidity to prevent overheating [108], which can degrade or damage sensitive electronics. Cloud Data Centers use advanced cooling strategies, such as those presented in Table 1. These systems must operate continuously and at scale, especially in high-density environments where thermal loads are extreme. Energy is consumed not only by compressors and fans but also by pumps and sensors. Inefficient HVAC operation leads to higher PUE, a key metric for energy performance in CDCs, which is presented in the next section.

Table 1. Comparison of CDC cooling strategies.

Cooling Strategy	Methodology	Advantages	Disadvantages	Examples
Air-Based Cooling	Uses CRAC or CRAH units to circulate air around servers.	Simple and widely adopted; low initial cost.	High energy consumption; inefficient for high-density workloads.	[109–116]
Cold/Hot Aisle Containment	Separates hot and cold air paths, using containment structures.	Improves energy efficiency and reduces hot spots.	Requires proper planning and layout; retrofitting is difficult.	[110,117–120]
Direct-to-Chip Liquid Cooling	Delivers coolant directly to components, such as CPUs, via cold plates.	High cooling efficiency; ideal for high-performance systems.	Higher cost; risk of leaks.	[121–126]
Immersion Cooling	Submerges components in dielectric fluid for heat transfer.	Excellent thermal performance; quiet operation.	Expensive setup; fluid compatibility and maintenance complexity.	[127–136]
Rear Door Heat Exchangers	Cooled water absorbs heat via coils mounted at the back of racks.	Scalable and effective for dense racks.	Adds rack weight; complex plumbing.	[137–145]
In-Row Cooling	Places cooling units between server racks for localized cooling.	Targeted cooling; reduces airflow inefficiencies.	High cost; depends on data center layout.	[146–156]
Evaporative Cooling	Uses evaporating water to pre-cool intake air.	Very energy-efficient in dry climates.	Ineffective in humid climates; water treatment needed.	[109,157–165]
Chilled Water Cooling	Chiller cools water that circulates through air handlers.	Suitable for large-scale operations; reliable.	Expensive infrastructure; needs regular maintenance.	[166–170]
Economizers	Uses outside air or water for cooling when ambient conditions allow.	Major energy savings; eco-friendly.	Weather-dependent; air filtration often required.	[171–180]
Hybrid Systems	Combines multiple cooling methods (such as air + liquid, or free cooling).	Flexible and efficient under varying loads.	High complexity and initial setup cost.	[123,140,180–190]

2.6. Facility Security, Lighting, and Offices

Security infrastructure restricts access to CDCs to authorized personnel, utilizing surveillance cameras [191], biometric access systems [192,193], motion sensors [194], alarms, and, occasionally, on-site monitoring rooms. Operating continuously with redundancies, backup power, and significant storage for video footage, these systems, while not major individual energy consumers, add to the facility's baseline power usage. As another energy consumer, lighting systems can be considered.

Lighting illuminates server rooms, offices, corridors, emergency exits, and outdoor areas in CDCs [195]. Although modern facilities use energy-efficient Light-Emitting Diode (LED) lights and smart controls, such as motion sensors and timers to reduce usage, lighting still contributes significantly to non-IT energy consumption. In large CDCs with multiple shifts or frequent maintenance, lighting's cumulative energy demand is substantial.

Cloud Data Center offices support staff including administrators, engineers, facility managers, and support teams, and they feature workstations, printers, telecommunication equipment, and often individual HVAC systems. While their energy use is lower than IT and cooling systems, these spaces contribute to non-IT energy consumption.

Based on the provided context about the energy-consuming components of a CDC, several energy efficiency metrics are useful in their efficient operation and management for considering usage, costs, overall efficiency, and sustainability. These metrics are presented in Section 3.

3. Energy Efficiency Metrics in Cloud Data Centers

Energy efficiency is the ratio of useful work output by a system to the total energy input [196–198]. In CDCs, this efficiency reflects the productive work carried out by various subsystems relative to the energy supplied [51]. To this end, we have divided these energy efficiency metrics into two classes:

1. IT-related metrics (Tables 2 and 3): Measurements that evaluate the energy performance of computing and networking components. These metrics assess how effectively IT resources utilize energy to perform computational tasks, focusing on the ratio of computational output to energy consumed, the degree of resource utilization, and the adaptability of power consumption to workload variations.
2. Non-IT-related metrics (Tables 4 and 5): These are used in the evaluation of supporting infrastructure such as power distribution, cooling systems, and building facilities. These metrics measure the proportion of energy used by non-IT systems relative to total energy consumption, with an emphasis on minimizing overhead and improving the efficiency of physical infrastructure and environmental controls.

Table 2. Cloud Data Center energy efficiency IT-related metrics information.

Metric	Definition	Primary Use	Examples
APC	Average power usage of IT equipment over time.	Monitors IT power trends.	[199–201]
CPE	Computes output per unit of IT power.	Measures IT computational efficiency.	[202–206]
DWPE	Workload processed per unit of IT power.	Workload efficiency at IT level.	[51,207]
EWR	Energy wasted per unit of computational work.	Energy cost of work.	[208,209]
ITEE	Efficiency of IT hardware.	Evaluates hardware efficiency.	[210–212]
OSWE	System workload output per total energy.	Measures system-level workload efficiency.	[51]
PpW	Performance per unit of power.	Measures IT hardware efficiency.	[213–216]
ScE	Server compute output per energy used.	Assesses server-level efficiency.	[217–219]
SPUE	PUE-like metric for servers.	Server-specific efficiency.	[220]
SWaP	Composite of performance vs. space and power.	Space–power performance balance.	[221–223]

Table 3. Cloud Data Center energy efficiency IT-related metrics mathematical details.

Metric	Formulation	Units	Best Value	Correlation with Other Metrics
APC	$\frac{\text{Total } IT \text{ Power}}{\text{Time}}$	W	Lower is better	↑ (ITEE), ↓ (PpW, CPE, ScE)
CPE	$\frac{\text{Compute Output}}{IT \text{ Power}}$	Ops/W	$+\infty$	↑ (PpW, ScE); ↓ (APC)
DWPE	$\frac{\text{Workload}}{IT \text{ Power}}$	Tasks/W	$+\infty$	↑ (ITEE, CPE); ↓ (APC)
EWR	$\frac{IT \text{ Energy}}{\text{Work Output}}$	kWh/Task	0	↓ (CPE, PpW, ScE); ↑ (APC)
ITEE	$\frac{\text{Rated Performance}}{\text{Rated Power}}$	%	1	↑ (PpW, CPE); ↓ (EWR)
OSWE	$\frac{\text{Workload}}{\text{Total System Energy}}$	%	1	↑ (DCeP, DCPE); ↓ (PUE)
PpW	$\frac{\text{Performance}}{\text{Power}}$	Perf/W	$+\infty$	↑ (CPE, ScE, ITEE); ↓ (EWR, APC)
ScE	$\frac{\text{Output}}{\text{Server Power}}$	Ops/W	$+\infty$	↑ (PpW, CPE, ITEE); ↓ (EWR)
SPUE	$\frac{\text{Total Server Energy}}{\text{Compute Energy}}$	%	1	↑ (PUE); ↓ (PpW, ScE)
SWaP	$\frac{\text{Performance}}{\text{Space} \times \text{Power}}$	Ops/m^{2}W	$+\infty$	↑ (DCPD); ↓ (EWR)

Table 4. Cloud Data Center energy efficiency non-IT-related metrics information.

Metric	Definition	Primary Use	Examples
CADE	Corporate-level efficiency	Corporate energy assessment	[51,224,225]
DCA	Data Center Availability	Measures uptime reliability	[226,227]
DCeP	Energy productivity	Productivity benchmark	[228]
DCgE	Green energy efficiency	Green energy impact	[51,221,228–230]
DCPD	Power density	Space optimization	[231]
DCPE	Performance per energy	Performance efficiency measure	[51,232]
DC-FVER	Fixed to variable energy	Cost structure insight	[233,234]
DH-UE	IT floor space utilization	Space optimization	[235]
DH-UR	Rack utilization rate	Rack deployment insight	[236–239]
EBS	Baseline comparison score	Tracks savings	[240–243]
H-POM	Non-computational (overhead) power consumed by hardware components	Includes everything consumed by the hardware	[244,245]
PDE	Power delivery efficiency	Power loss assessment	[51,246]
PEsavings	Energy efficiency savings	Savings tracking	[199,247]
SI-POM	Infrastructure optimization	Infrastructure focus	[51]
TUE	Holistic utilization	Total resource usage	[248]
PUE	Total vs IT energy	Efficiency benchmark	[36,249–255]
DCiE	Infra efficiency	Infrastructure energy ratio	[206,256]
CUE	Carbon emissions per IT energy	Carbon footprint metric	[257]

According to Tables 2 and 3, several sets of correlations are created, where improving one metric impacts others positively or negatively. Reducing APC positively correlates with ITEE, meaning lower power usage enhances efficiency of rated performance per power. However, it negatively correlates with PpW, CPE, and ScE, as cutting power may reduce performance or compute output, worsening these metrics that aim for higher values. Conversely, improving CPE, which measures compute output per IT power and targets higher values, positively correlates with PpW and ScE, indicating that better compute efficiency boosts performance and server efficiency, but it negatively correlates with APC, as higher compute output may increase power usage. DWPE shows positive correlations with ITEE and CPE, suggesting higher workload efficiency aligns with better equipment and compute efficiency, but it negatively impacts APC. EWR, where lower is better, negatively correlates with CPE, PpW, and ScE, meaning less energy per task improves these performance metrics, but it positively correlates with APC, as lower energy use may reflect higher power consumption. ITEE positively correlates with PpW and CPE but negatively with EWR, indicating efficient equipment supports performance but it may increase energy per task. OSWE positively correlates with Data Center energy Productivity (DCeP) and Data Center Performance Efficiency (DCPE) but negatively with PUE, suggesting system-wide efficiency improvements conflict with PUE optimization. PpW and ScE share

strong positive correlations with each other, CPE, and ITEE, but they negatively correlate with the EWR and APC, reinforcing their alignment with performance efficiency. SPUE positively correlates with PUE but negatively with PpW and ScE, indicating trade-offs in server energy distribution. Finally, SWaP positively correlates with Data Center Power Density (DCPD) but negatively with the EWR, showing that optimizing performance per space and power aligns with density. However, it may increase energy per task.

Table 5. Cloud Data Center energy efficiency non-IT-related metrics mathematical details.

Metric	Formulation	Best Value	Units	Correlation with Other Metrics
CADE	$\frac{\text{IT Asset Utilization} \times DCiE}{\text{IT Capacity} \times \text{Facility Energy}}$	1	Ratio	↑ (ITEU, DCiE); ↓ (PUE)
DCA	$\frac{\text{Uptime}}{\text{Total Time}}$	1	Ratio	↓ PUEreliability
DCeP	$\frac{\text{Useful Work}}{\text{Total Facility Energy}}$	1	Output/W	↑ (DCPE, OSWE); ↓ (PUE)
DCgE	$\frac{\text{Renewable}}{\text{Total Energy}} \times DCiE$	1	Ratio	↑ (GEC, DCiE); ↓ (CUE)
DCPD	$\frac{\text{IT Power}}{\text{Floor Area}}$	Higher varies	W/m^2	↑ (SWaP); ↓ (RCI)
DCPE	$\frac{\text{Output}}{\text{Facility Energy}}$	1	Output/W	↑ (DCeP, OSWE); ↓ (PUE)
DC-FVER	$\frac{\text{Fixed}}{\text{Variable Energy}}$	Lower is better	Ratio	↓ (CER)
DH-UE	$\frac{\text{Active Floor}}{\text{Total Hall}}$	1	Ratio	↑ (DH-UR, TUE)
DH-UR	$\frac{\text{Deployed Racks}}{\text{Total Racks}}$	1	Ratio	↑ (DH-UE, TUE)
EBS	$\frac{\text{Actual}}{\text{Baseline}}$	1	Ratio	↑ (PUE); ↓ (PEsavings)
H-POM	Custom Formula	1	Ratio	↑ (ITEU, GEC, DCiE); ↓ (PUE)
PDE	$\frac{\text{IT Power}}{\text{Input Power}}$	1	Ratio	↑ (DCiE); ↓ (PUE)
PEsavings	$\frac{\text{Baseline} - \text{Current}}{\text{Baseline}}$	1	Ratio	↑ (DCiE); ↓ (PUE, EBS)
PUEreliability	$\frac{\text{Total} - \text{Redundancy}}{\text{IT Energy}}$	1	Ratio	↑ (PUE); ↓ (DCA)
SI-POM	Custom formula	1	Ratio	↑ (CER, PDE); ↓ (PUE)
TUE	$\frac{ITEU \times DH-UR \times DCiE}{100}$	1	Ratio	↑ (ITEU, DH-UR, DH-UE); ↓ (PUE)
PUE	$\frac{\text{Total Power}}{\text{IT Equipment Energy}}$	1	Ratio	↓ (DCiE, PDE); ↑ (CUE)
DCiE	$\frac{\text{IT}}{\text{Total Facility Energy}}$	1	Ratio	↑ (PDE); ↓ (PUE)
CUE	$\frac{CO_2}{\text{IT Equipment Energy}}$	0	$KgCO_2/kWh$	↑ (PUE)

About non-IT-related metrics (Tables 4 and 5), the Corporate Average Data center Efficiency (CADE) metric, which targets a value of 1, positively correlates with the IT Equipment Utilization (ITEU) and DCiE, indicating that higher IT asset utilization and IT energy efficiency improve asset deployment efficiency. Still, it negatively correlates with PUE, as better asset efficiency often increases total facility power relative to IT power. The Data Center Availability (DCA) metric, also aiming for 1, negatively correlates with PUE Adjusted for Reliability (PUEreliability), suggesting that maximizing uptime may compromise reliability adjustments for power usage. The Data Center energy Productivity (DCeP) metric, targeting 1, positively correlates with DCPE and OSWE, showing that increased useful work per facility energy aligns with output efficiency and system workload efficiency, but it negatively correlates with PUE, as higher work output may elevate total power. Similarly, DCPE, also targeting 1, mirrors these correlations with Data Center Energy Productivity (DCeP), OSWE, and PUE. The Data Center green Efficiency (DCgE) metric, aiming for 1, positively correlates with Green Energy Coefficient (GEC) and DCiE, indicating that greater renewable energy use enhances green energy contributions

and IT efficiency, but negatively correlates with CUE, as renewable energy reduces CO_2 emissions. The DCPD metric, where higher values vary by context, positively correlates with SWaP, suggesting that higher IT power density supports space-adjusted performance, but negatively correlates with the Rack Cooling Index (RCI), as dense power usage may strain cooling infrastructure.

The Data Center Fixed to Variable Energy Ratio (DC-FVER) metric, where lower is better, negatively correlates with the Cooling Effectiveness Ratio (CER), indicating that reducing fixed-to-variable energy ratios conflicts with cooling efficiency. The Data Hall Utilization Efficiency (DH-UE) and Data Hall Utilization Rate (DH-UR) metrics, both targeting 1, positively correlate with each other and Total Utilization Efficiency (TUE), reflecting that active floor and rack deployment efficiencies enhance total utilization but lack negative correlations in the table. The Energy Baseline Score (EBS) metric, aiming for values less than 1, positively correlates with PUE, suggesting that lower energy baselines align with higher facility-to-IT power ratios, but it negatively correlates with Power Efficiency Savings (PEsavings), as reduced actual energy hinders savings potential. The Hardware Power Overhead Multiplier (H-POM) metric, targeting 1, positively correlates with ITEU, GEC, and DCiE, indicating that holistic performance aligns with utilization and green efficiency, but it negatively correlates with PUE. The Power Delivery Efficiency (PDE) and PEsavings metrics, both aiming for 1, positively correlate with DCiE and negatively with PUE, showing that efficient power delivery and energy savings enhance IT efficiency but increase facility power ratios. The PUEreliability metric, targeting 1, positively correlates with PUE but negatively with DCA, reflecting trade-offs between reliability and uptime. The System Infrastructure Power Optimization Metric (SI-POM) metric, also aiming for 1, positively correlates with CER and PDE but negatively with PUE, indicating that site infrastructure efficiency supports cooling and power delivery but conflicts with PUE. The TUE metric positively correlates with ITEU, DH-UR, and DH-UE, reinforcing utilization efficiencies, but it negatively correlates with PUE. Finally, PUE, DCiE, and CUE form a tight correlation cluster: DCiE positively correlates with PDE and negatively with PUE, while PUE negatively correlates with DCiE and positively with CUE, and CUE positively correlates with PUE, highlighting that minimizing CO_2 emissions and maximizing IT efficiency often increases the facility-to-IT power ratio.

4. Real-World Examples

The proposed metrics are used in corporations' (such as Google's or Microsoft's) CDC energy-efficient management. For instance, in 2023 Google reported an average annual PUE of 1.10 across its global fleet of large-scale CDCs, lower than the industry average of 1.58 [258]. Microsoft tracks PUE and WUE to monitor energy and water efficiency in its data centers. For the period from 1 July 2023 to 30 June 2024, Microsoft reported PUE and Water Usage Effectiveness (WUE) figures for its operational CDCs, emphasizing location-specific variables such as climate and humidity. A recent Microsoft study also highlighted that advanced cooling methods, such as cold plate and immersion cooling, can reduce data center emissions and water usage, particularly for AI workloads [259].

PayPal improved its CDC efficiency by adopting NVIDIA's accelerated computing, reducing server energy consumption by nearly eight times while enhancing real-time fraud detection. This highlights how workload-specific efficiency improvements can be measured beyond traditional metrics such as PUE, as it is just the first step [260].

5. Challenges and Future Works

This section offers challenges and future scope for CDCs.

5.1. Challenges

5.1.1. IT-Related Metrics

Of the presented IT-related energy efficiency metrics CDCs, each faces challenges and limitations in quantifying power usage and performance in modern computing environments, as shown in Figure 8. APC struggles with the dynamic variability of cloud workloads, complicating consistent tracking, and it fails to reflect the productivity of power used, limiting its efficiency insights. CPE is challenged by the heterogeneity of cloud tasks, making computational output measurement complex, and overlooking the non-computational factors of memory and storage, missing a holistic view. DWPE grapples with consistently defining workloads across virtualized platforms and is sensitive to measurement timing, leading to inconsistent results. EWR faces difficulties in distinguishing wasted from useful energy and struggles to objectively assess task usefulness in mixed environments. ITEE's efficiency varies with workload types, hindering cross-platform comparisons, and it ignores software or system management inefficiencies. OSWE finds it hard to define system boundaries in distributed cloud settings and does not distinguish between idle and active states. PpW is affected by workload diversity, making comparisons misleading, and it lacks standardized baselines for reliable benchmarking. ScE is complicated by workload distribution layers, missing broader data center interactions, while SPUE's limited industry adoption and architecture-specific dynamics reduce its comparability. Lastly, SWaP tackles the conflicting optimization of space, power, and performance, with challenges in defining trade-offs and achieving automatic tuning.

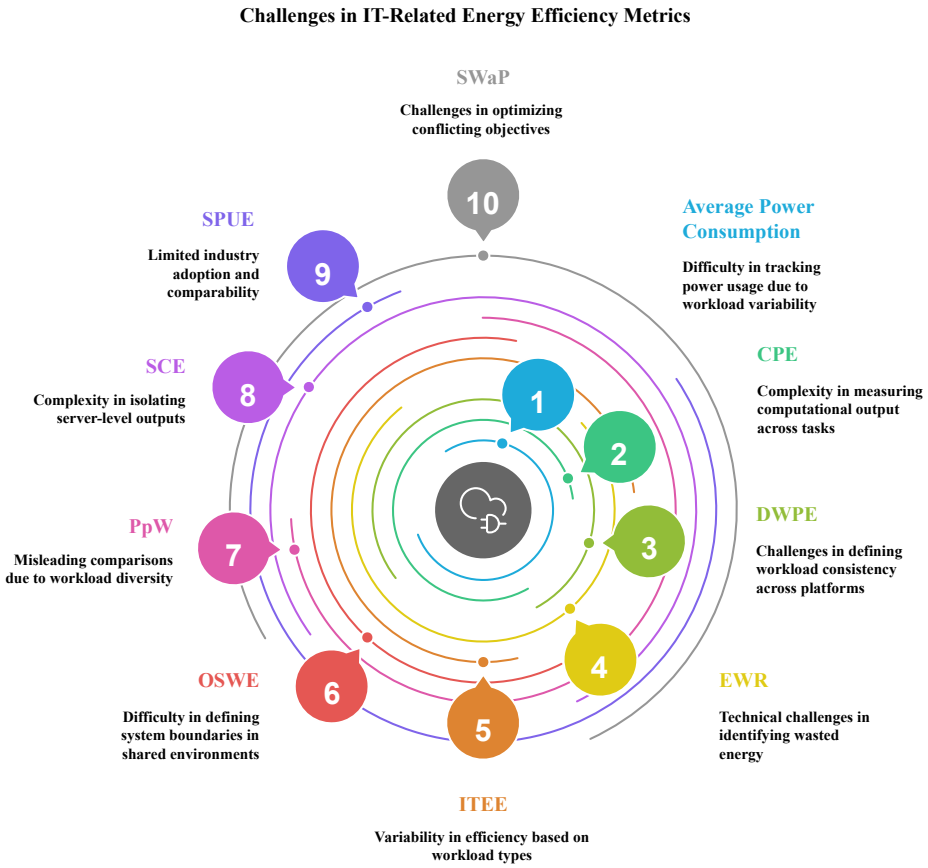


Figure 8. Challenges and limitations of the presented IT-related energy efficiency CDC metrics.

5.1.2. Non-IT-Related Metrics

The related challenges for non-IT-related metrics are manifested in Figure 9.

Corporate Average Data Center Efficiency faces the challenge of aggregating data across diverse sites with varying architectures and operational models, which complicates consistent measurement. Its limitation lies in potentially masking inefficiencies at individual data centers due to the averaging effect, reducing its ability to pinpoint specific issues. DCA struggles with balancing energy efficiency against the need for high uptime, often leading to conservative, less efficient designs. However, it is limited as a reliability metric rather than an efficiency one, as it does not measure how efficiently availability is achieved.

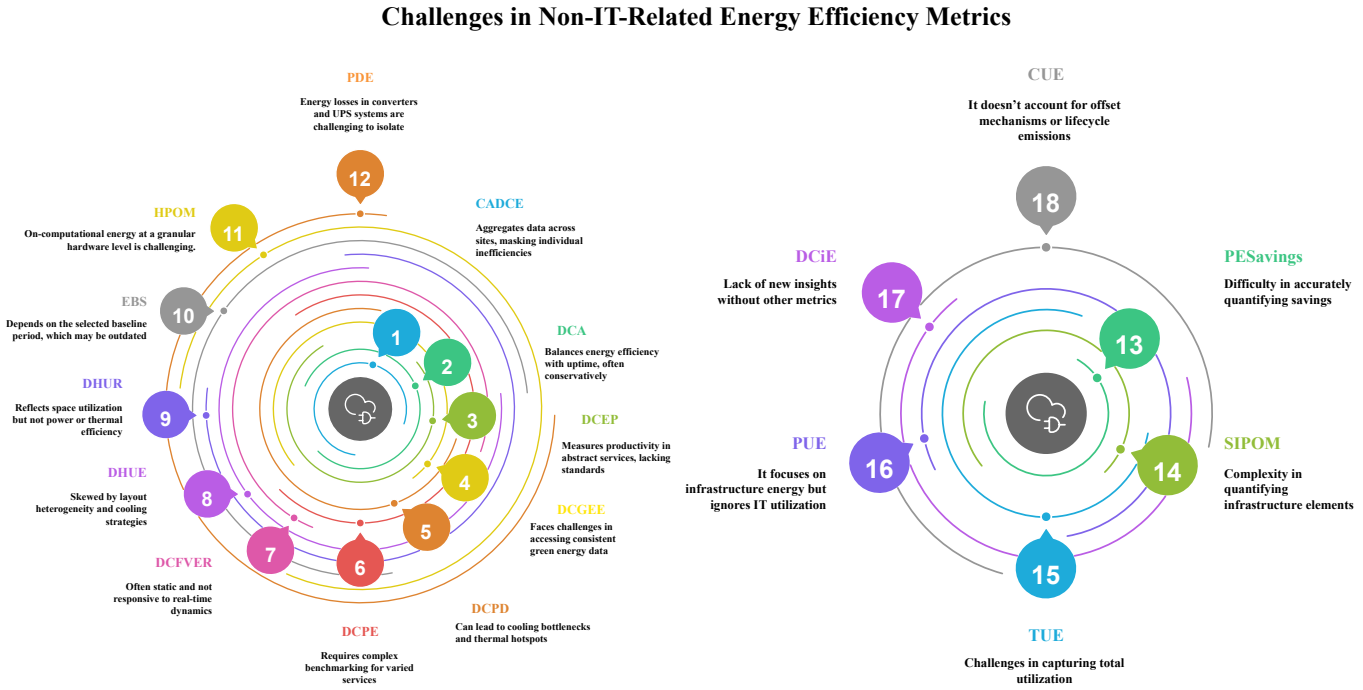


Figure 9. Challenges and limitations of the presented non-IT-related energy efficiency CDCs metrics.

Data Center Energy Productivity encounters difficulties in standardizing the measurement of productivity for abstract services such as cloud functions, lacking a universal approach. Its limitation is the challenge of correlating energy input with meaningful service output in a generalized manner, reducing its applicability. Data Center green Efficiency (DCgE) is hindered by restricted access to consistent, verifiable green energy data, and its limitation lies in not accounting for the intermittent availability of green sources or energy storage inefficiencies, which can skew results.

Data Center Power Density faces challenges with cooling bottlenecks and thermal hot spots caused by higher density designs. Its limitation is that it may prioritize compact layouts at the expense of cooling efficiency and maintainability, leading to operational trade-offs. DCPE requires complex performance benchmarking for diverse services in hybrid environments, and its lack of a universal performance definition limits comparability across data centers.

Data Center Fixed to Variable Energy Ratio demands granular instrumentation to distinguish fixed from variable energy components, a challenging task. Its static nature, not responsive to real-time load changes, is a key limitation. DH-UE is affected by layout heterogeneity and varying cooling strategies, which can distort utilization measurements, and it overlooks vertical space and cooling zones, providing an incomplete view of spatial efficiency.

Data Hall Utilization Rate lacks real-time rack-level monitoring and vendor standardization, limiting its precision. It only reflects space utilization, ignoring power or thermal efficiency, which restricts its scope. EBS struggles to establish reliable baselines in

dynamic cloud environments, and its dependence on potentially outdated baseline periods undermines its relevance.

Power Efficiency Savings faces the challenge of quantifying savings through estimates rather than measured outcomes, and without a standard reference claimed savings may be inflated or inconsistent. SI-POM is intricate to quantify in shared facilities and lacks real-time tracking, missing transient inefficiencies.

Total Utilization Efficiency is complex to measure, due to factors of idle time, redundancy, and oversubscription, and its broad, aggregate nature reduces its actionability. PUE can be manipulated (such as by shutting off unused equipment) and is often reported under optimal conditions, while its focus on infrastructure energy ignores IT utilization, leading to potential misinterpretation.

Data Center Infrastructure Efficiency has limited new insights unless combined with other metrics, and it fails to capture internal inefficiencies in IT or cooling subsystems. Finally, CUE requires access to often unavailable or approximate CO_2 emissions data from energy providers, and its exclusion of offset mechanisms or lifecycle emissions results in an incomplete environmental assessment.

5.2. Future Works

5.2.1. IT-Related Metrics

For APC, future work will focus on creating intelligent, workload-aware tools that dynamically adjust power metrics in real time, based on specific system parameters. These tools will incorporate system utilization rates, hardware degradation over time, and cooling system dynamics, while leveraging AI models to predict and optimize energy consumption proactively with high accuracy. For CPE, the goal is to establish standardized computational output units tailored to diverse applications, ensuring precise alignment of power consumption with specific compute tasks. Adaptive models are proposed to dynamically quantify the computational value of heterogeneous workloads, improving energy efficiency in real-time operational scenarios.

Data Center Workload Power Efficiency focuses on establishing universal workload definitions and standardized benchmark suites to ensure consistent, reproducible evaluation across diverse computing platforms. Automated profiling tools are recommended to enhance workload tagging and power consumption traceability, enabling precise, real-time assessments of energy efficiency. For EWR, the objective could be to develop refined methods for categorizing energy wastage, clearly distinguishing between essential and non-essential energy consumption under varying workload conditions. Artificial Intelligence techniques could be proposed to identify inefficiency patterns and recommend targeted system-level optimizations to minimize energy waste.

IT Equipment Energy Efficiency aims to integrate software performance indicators and real-time workload classification to enable comprehensive efficiency assessments. It promotes hardware–software co-design strategies to optimize performance by aligning computational demands with resource utilization. OSWE focuses on decomposing energy consumption into active, idle, and background categories through fine-grained telemetry, while mitigating virtualization and orchestration overhead in cloud-native environments to enhance overall system efficiency.

Performance per Watt advancements focus on developing workload-specific databases to inform precise system configurations and utilizing machine learning to dynamically optimize operations for maximum energy efficiency in real time. Server Compute Efficiency emphasizes detailed intra-server monitoring, including per-core and per-thread performance analysis, and explores correlations between compute efficiency, thermal dynamics, and performance throttling to enhance server-level optimization.

Server Power Usage Effectiveness could be in alignment with comprehensive PUE metrics, emphasizing the development of automated reporting tools and dashboard integration for real-time efficiency tracking. SWaP proposes multi-objective optimization and AI-driven decision frameworks to effectively balance trade-offs between space utilization, power consumption, and computational performance. The use of Digital Twin (DT) models makes it possible to simulate and validate SWaP strategies before implementation, improving decision-making precision.

5.2.2. Non-IT-Related Metrics

The future development of non-IT-related data center energy efficiency metrics will focus on three primary directions: (1) enhancing standardization by defining uniform calculation methodologies for metrics such as facility energy re-use and cooling efficiency across geographic and regulatory boundaries; (2) automating data collection and analysis through integration with building management systems, Internet of Things (IoT) sensors, and AI-based anomaly detection; and (3) using advanced technologies such as digital twins and predictive analytics to provide dynamic and scenario-based insights into infrastructure performance. For Corporate Average Data center Efficiency (CADE), upcoming efforts could emphasize the creation of standardized cross-organizational key performance indicators that account for energy use in auxiliary systems (such as lighting, HVAC, security) and align with Environmental, Social, and Governance (ESG) requirements, enabling consistent corporate-level reporting of environmental performance. DCA initiatives could increasingly incorporate energy-aware reliability models by quantifying the trade-offs between power consumption and system availability (such as the impact of redundancy level versus efficiency), supported by real-time telemetry and AI-driven predictive maintenance to optimize uptime without excess energy overhead.

For DCeP, the focus will shift toward automated, workload-aware productivity measurement using real-time operational data (task completion rate, computational throughput per energy unit), while ensuring alignment with changing industry performance benchmarks, such as output-based metrics, to enable accurate and continuous evaluation of energy-to-output efficiency.

Data Center green Efficiency will advance by implementing blockchain-based or smart contract systems for green energy traceability, enabling verifiable tracking of renewable energy inputs at a granular level, while also incorporating comprehensive Lifecycle Assessments (LCAs)—including embodied carbon and end-of-life emissions—to offer a more accurate evaluation of environmental impacts. DCPD will prioritize thermal-aware high-density architecture design, using Computational Fluid Dynamics (CFD) simulations and liquid cooling integration to mitigate hot spots and improve heat dissipation efficiency in rack-scale deployments. DCPE aims to utilize AI-driven adaptive performance models—such as reinforcement learning and digital twin simulation—to dynamically predict and balance workloads against energy consumption profiles, optimizing the energy-performance trade-off in near real-time. DC-FVER will refine cost allocation frameworks by incorporating time-of-use energy pricing models and real-time consumption data and by integrating with smart grid interfaces, enhancing cost traceability and enabling demand-side response participation. DH-UE and DH-UR will automate space and rack usage tracking through RFID, computer vision, and occupancy sensors, while optimizing modular hardware design and resource allocation through constraint-aware algorithms to maximize spatial and operational efficiency.

EBS development will focus on automated baseline recalibration using historical and streaming operational data, supported by predictive analytics to detect deviation trends and ensure that energy performance benchmarks remain relevant over time. H-POM intends

to implement sub-component-level power telemetry (e.g., PSU-level, network interface cards) and develop standardized power overhead metrics, allowing for detailed attribution of energy use across hardware elements. PDE can enhance power delivery architectures by incorporating high-efficiency DC–DC conversion, busbar optimization, and real-time loss-tracking algorithms to minimize distribution inefficiencies within the data center power path. PEsavings may enable automated energy savings quantification by linking real-time energy data with dynamic cost models, providing finance and sustainability teams with clearer, auditable insights into cost-to-efficiency benefits. SI-POM can consider using IoT networks for fine-grained, edge-level monitoring of power and thermal systems, enabling closed-loop control schemes to reduce overcooling and improve power delivery precision. TUE will focus on building AI-assisted unified utilization frameworks that incorporate compute, memory, storage, and networking usage data to improve global resource scheduling and holistic system efficiency. PUE will be refined to consider workload type and utilization context, with hybrid metrics that integrate CO_2-equivalent emissions per compute output to better align efficiency reporting with carbon accountability. DCiE development will emphasize real-time analytics platforms that correlate infrastructure energy usage with renewable input and cooling efficiency data to deliver more actionable, infrastructure-level insights. Finally, CUE can be evolved by standardizing carbon emissions reporting methodologies, including Scope 2 emissions, and integrating renewable energy certificates and time-stamped carbon intensity data to improve the accuracy and consistency of data center CO_2 footprint assessments.

6. Conclusions

In this study, various components contributing to energy consumption within CDCs, including UPS and PDU configurations, as well as diverse energy efficiency metrics, have been systematically examined. The analyzed metrics offer critical insights into optimizing resource utilization, reducing energy waste, and ensuring compliance with environmental and regulatory standards. By addressing the inherent challenges and limitations of these metrics and exploring prospective research avenues—particularly the integration of AI technologies—further enhancements in energy efficiency could be realized. Advancements in this domain not only promise cost reductions and lower carbon emissions but also support the scalability and sustainability of digital services, fostering a more resilient and environmentally conscious digital infrastructure.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
AI	Artificial Intelligence
APC	Average Power Consumption
CADE	Corporate Average Data center Efficiency
CAGR	Compound Annual Growth Rate
CDC	Cloud Data Center
CER	Cooling Effectiveness Ratio
CPE	Compute Power Efficiency
CPU	Centeral Processing Units
CRAC	Computer Room Air Conditioning
CRAH	Computer Room Air Handler
CUE	Carbon Usage Effectiveness
DC	Direct Current
DC-FVER	Data Center Fixed to Variable Energy Ratio
DCA	Data Center Availability
DCeP	Data Center energy Productivity
DCgE	Data Center green Efficiency
DCiE	Data Center infrastructure Efficiency
DCPD	Data Center Power Density
DCPE	Data Center Performance Efficiency
DH-UE	Data Hall Utilization Efficiency
DH-UR	Data Hall Utilization Rate
DT	Digital Twin
DWPE	Data Center Workload Power Efficiency
EBS	Energy Baseline Score
ESG	Environmental, Social, and Governance
EWR	Energy Wastage Ratio
GEC	Green Energy Coefficient
GPU	Graphical Processing Unit
H-POM	Hardware Power Overhead Multiplier
HVAC	Heating, Ventilation, and Air Conditioning
IEA	International Energy Agency
IoT	Internet of Things
IT	Information Technology
ITEE	IT Equipment Energy Efficiency
ITEU	IT Equipment Utilization
LED	Light-Emitting Diode
LIB	Lithium-Ion Battery
NN	Neural Network
NSERC	Natural Sciences and Engineering Research Council of Canada
OSWE	Operational System Workload Efficiency
PDE	Power Delivery Efficiency
PDU	Power Distribution Unit
PEsavings	Power Efficiency Savings
PPA	Power Purchase Agreement

PpW	Performance per Watt
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
PUE	Power Usage Effectiveness
PUEreliability	PUE Adjusted for Reliability
RAM	Random Accessible Memory
RCI	Rack Cooling Index
RES	Renewable Energy Source
ScE	Server compute Efficiency
SI-POM	System Infrastructure Power Optimization Metric
SPUE	Server Power Usage Effectiveness
SWaP	Space, Wattage, and Performance
TUE	Total Utilization Efficiency
UPS	Uninterruptible Power Supply
VM	Virtual Machine
WUE	Water Usage Effectiveness

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