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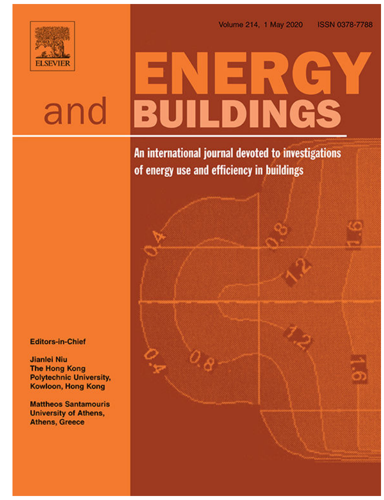

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A Review of Energy Efficiency Evaluation Technologies in Cloud Data Centers

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ABSTRACT

The energy consumption by data centers is expanding in tandem with the rapid rise of the digital economy. Data centers, as high-energy-consumption organizations, have garnered extensive attention from society in order to accomplish energy conservation and emission reduction. As a result, improving the energy efficiency of cloud data centers has become a major topic of research. Researchers are working hard to develop practical energy efficiency evaluation methodologies and metrics in order to attain this goal. This article summarizes data center energy efficiency evaluation methods, classifies existing energy efficiency evaluation metrics, examines the current state and challenges of data center energy efficiency evaluation, and makes recommendations for improving energy efficiency evaluation technology to assist cloud operators, decision-makers, and researchers in developing appropriate energy efficiency evaluation strategies. We give data center researchers a better grasp of energy efficiency evaluation and encourage them to combine theory and practice in energy efficiency evaluation and utilize more advanced metrics to assess data center energy efficiency. This is a critical step in the quest for the most advanced green technology, as well as a significant step toward reaching sustainable development goals.

1. Introduction

The world as a whole is embarking on a major revolution from the actual to the digital economy. The fundamental support for smart city management and industrial digitization is data, which is the primary production component of the digital economy. With the commercialization of 5G and the rise of artificial intelligence, more large-scale data will be generated. Data center capacity is quickly rising over the world, and this is especially true in China [1]. According to statistics from [2], the main data industry will account for 15% of total economic volume by 2030, and China's total data would exceed 4YB, accounting for 30% of world total data. According to Canalys data, service spending on worldwide cloud infrastructure climbed by 35% to $41.8 billion in the first quarter of 2021. This is an increase of nearly 11 billion dollars over the first quarter of 2020 [3].

However, as data center sizes grew, so did their power consumption, which soared at an alarming rate every year. The Amsterdam metropolitan government in the Netherlands banned the construction of new data centers because the rapid growth in the number of data centers in metropolitan areas has resulted in insufficient space and significant demand on the power grid [4]. Each year, data centers in the United States require more than 90 billion kilowatt-hours of electricity, necessitating the construction of 34 large-scale (500 MW) coal-fired power plants. Global data center energy consumption is over 416 terawatts (around 3% of total electricity), and it doubles every four years [5]. Some studies have confirmed the consensus [6, 7, 8] that data center electricity demand will rise from 200 billion kWh in 2010 to 2,000 to 3,000 billion kWh by 2030. Meanwhile, the rate of increase in the global carbon footprint is alarming. Because the data center is an increasing power-intensive industry and a carbon emission giant in the Internet era, it is needless to explain the importance of energy efficiency research. Data center energy efficiency evaluation has piqued the interest of data center operators, decision-makers, and researchers due to the high energy consumption behavior of data centers. It is vital to understand the energy consumption composition and hierarchical structure of the data center before undertaking energy efficiency evaluation research. Figure 1 depicts the power consumption of various components in data centers in the United States, which shows that servers account for 43% of the total, followed by the storage driver. Despite the fact that network devices make up only 3% of the total, they must not be overlooked.

IT equipment and physical infrastructure make up the majority of data centers. The physical infrastructure primarily consists of power supply and temperature control systems. Figure 2 depicts the relationship model. All IT equipment must be operated with extraordinary dependability at all times. The temperature control equipment mostly consists of air conditioning, heating, ventilation, and other similar items. The temperature control is primarily employed to avoid overheating caused by the enormous quantity of heat created by IT equipment during operation, which also uses a significant amount of additional electricity. The power supply facilities in data centers mainly include UPS, PDU transformers, connectivity(cabling) and backup generators, etc. Servers, storage, and networks are the most common

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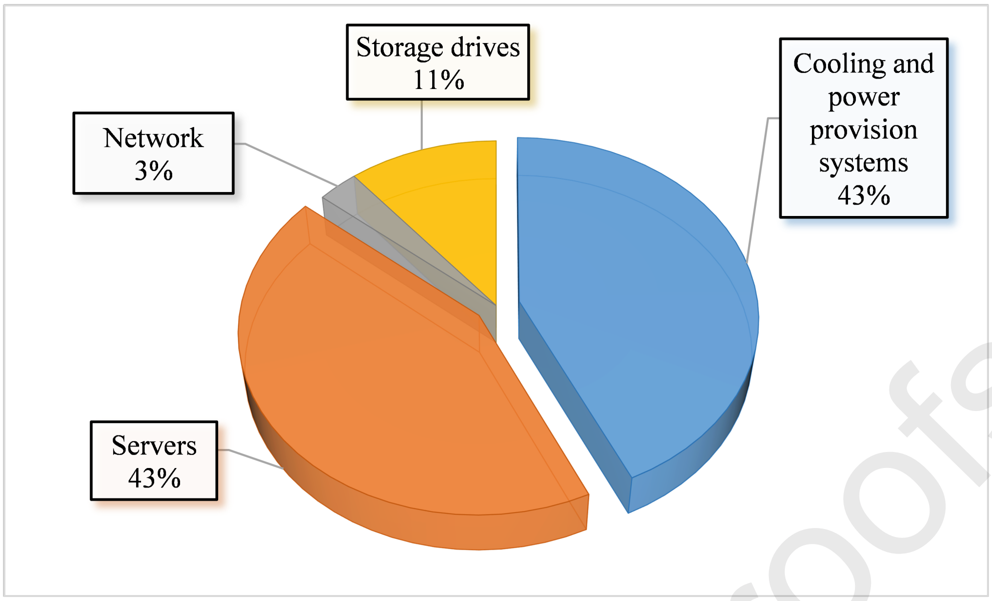

Figure 1: Fraction of electricity used by US data centers in 2014 [1, 9].

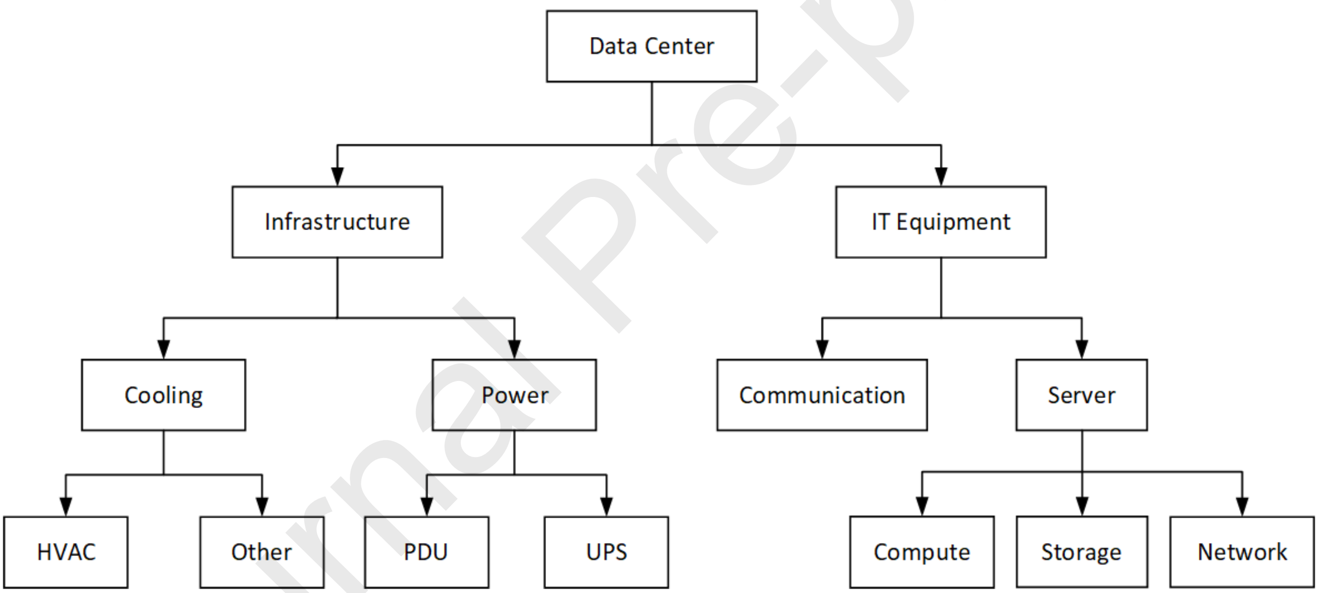

Figure 2: Data center hierarchy diagram.

types of IT equipment, according to [10]. Because of the various application scenarios in different data centers, the classification of IT equipment is slightly different. According to several studies [11, 12], IT equipment is primarily made up of servers arranged in racks. Application servers, storage servers, and network devices such as switches, routers, and other network devices are among the servers [13]. Unlike other articles, Dayarathna et al. [14] advocated that IT equipment should be classified based on the kind of hardware components, taking into account the primary sources of energy consumption. IT systems should be split between hardware and software, according to several reviews [14, 15]. The hardware is divided into three parts: Server Tier, Storage Tier, and Network Tier, which correspond to the three main components: servers, storage drives, and networks.

Data center operators spend a lot of money on electricity. More effective measures are needed to establish a healthy link between human development and environmental preservation, given the high loss rate and high energy consumption of the data center industry. Effective energy efficiency evaluation methods and standards are required for the data center industry to achieve its objectives. Researchers in data centers can come up with a variety of strategies to lower the data center's energy usage [16, 17, 18]. When energy consumption decreases, how do we know whether the reduction in energy consumption will affect the performance of

Table 1
Summary of the review articles on data center energy efficiency

Classification	Theme	Years	Ref
Energy efficiency	The State of Practice of Power Measurement and Energy Efficiency Technology in the Data Center Industry	2016	[21]
Thermal management	Different levels of thermal performance evaluation metrics for data centers	2020	[22]
Energy efficiency	Energy efficiency and demand response of small and medium data centers	2018	[23]
Thermal management	Thermal management and evaluation technology for data centers and related cooling systems	2018	[24]
Metric performance	Green performance metrics for data center environmental performance	2013	[9]
Energy efficiency	The main technology of cloud computing energy saving	2016	[25]
Thermal management	The impact of airflow on the thermal environment and energy efficiency of data centers	2019	[26]
Thermal management	Data center air conditioning energy performance standards	2017	[27]
Metric performance	Defects and improvement directions of PUE metrics	2016	[28]
Energy consumption of components	Power consumption modeling and optimized control strategy of cooling system	2021	[29]
Energy consumption of components	Energy consumption model and modeling method of cloud server	2020	[30]
Energy consumption of components	The impact of mechanisms used at the hardware component level on data center power consumption	2021	[31]

the data center? Energy efficiency evaluation is a method to effectively measure energy utilization and provides guidance for energy conservation in data centers [19, 20]. Therefore, the energy efficiency evaluation of data centers is considered to be one of the most concerned research points for cloud operators.

Table 1 lists survey articles about data center energy efficiency so far. It can be found that most of the reviews focus on energy efficiency, metric performance, thermal management and component energy consumption. The energy efficiency reviews focused on analyzing the energy distribution of the data center and energy efficiency improvement technologies. For example, virtualization technology and energy-aware scheduling. However, there are few introductions to evaluation metrics and evaluation methods. The reviews of metric performance mainly focuses on energy efficiency evaluation metrics, and less summary of energy efficiency evaluation methods. We summarized the metrics in three granularities, and then analyzed the advantages and disadvantages of commonly used metrics, especially PUE. The reviews of thermal management and component energy consumption mainly focused on part of the energy efficiency of the data center. This review is dedicated to energy efficiency evaluation techniques for data centers. We summarized the methods and metrics of data center energy efficiency evaluation, and discussed the current status, challenges and recommendations of energy efficiency evaluation. The main contributions are as follows:

1) We summarized the three approaches for evaluating data center energy efficiency and compared their benefits and drawbacks. For energy efficiency evaluation, a multi-metric fusion evaluation was recommended.

2) We analyzed the current state of energy efficiency evaluation technology in industry and academia, and gave recommendations to data center operators, decision-makers, and researchers.

3) We summarized the data center energy efficiency evaluation metrics, as well as their benefits and drawbacks, so that users could select the most relevant metrics. Then we looked at the problems in the existing energy evaluation metrics and made recommendations for improving and inventing new PUE metrics.

The remainder of this paper is organized as follows. Section 2 describes the three approaches for evaluating data center energy efficiency and compares and contrasts their benefits and drawbacks. Section 3 summarizes the energy efficiency evaluation metrics of data centers and analyzes the benefits and drawbacks of commonly used metrics, particularly PUE. Section 4 analyzes the current state and challenges of energy efficiency evaluation, and provides a reference for the next step of research in the field. Section 5 put forward suggestions to improve energy efficiency evaluation technology in order to cope with the development of data centers. Section 6 summarizes the article and gives recommendations for data center operators, decision-makers, and researchers in terms of future directions.

2. Energy efficiency evaluation methods

The present physical data center and the data center to be developed must both be considered when evaluating data center energy efficiency. The methods for evaluating energy efficiency are summarized in this section. Approaches for evaluating data center energy efficiency can be split into

Table 2
Measurement method of energy efficiency metrics

Measurement method	Study focus	Ref
Linear function	Measurement of power consumption of multi-component based on cloud server in heterogeneous cloud environment	[36]
Machine learning	Prediction of key performance metrics related to data center power efficiency	[37]
Machine learning	Performance metric of HPC data center's hot water cooling circuit	[38]
Expert system based on trust rules	Prediction of data center power utilization efficiency (PUE)	[39]
Linear function	A framework for rapid estimation of application energy consumption in data centers	[40]

three categories: measurement-based methods, simulation-based methods, and analytical modeling-based methods [32, 33]. The measurement-based evaluation is the most accurate of the three. The accuracy of the simulation-based evaluation is the lowest.

2.1. Measurement-based evaluation

At present, energy efficiency evaluation is mainly completed by a combination of short-term on-site measurements and engineering calculations. Measurement-based evaluation is the most intuitive, basic and accurate method. However, the measurement process requires a lot of manpower and financial resources. To measure metrics linked to data center energy efficiency, this method normally necessitates the use of specialized equipment. For example, researchers frequently utilize a Power Distribution Unit (PDU) to measure the power consumption of IT devices. Every measuring instrument has a certain degree of inherent error. Some researchers have attempted to develop novel measurement methods in order to increase the accuracy of measurement equipment. Some measurement methods are shown in Table 2. The accuracy of measurement evaluation depends not only on the accuracy of the measurement equipment, but also on the evaluation metrics. PUE was proposed as an energy efficiency indicator for data centers by the US Green Grid Organization in 2007[34]. PUE is frequently utilized in the data center industry as a simple and easy-to-use evaluation metric [35]. However, because to the limits of PUE, data centers may only be evaluated in this manner in a rough sense. Furthermore, measurement-based evaluation methods are only applicable to systems that are already in place. We'll go over energy efficiency evaluation metrics in more detail in Section 3. In the realm of data centers, there is currently no approved measurement method. Central and Eastern European countries have developed a set of energy efficiency evaluation guidelines based on actual measurements[1], but only focus on water resource utilization and carbon emissions, not data center energy efficiency.

2.2. Simulation-based evaluation

It is difficult to evaluate the solution in a real setting when dealing with large-scale computing systems, which is a significant drawback in evaluating data center energy efficiency. To circumvent this constraint, simulation tools have rapidly become the most common way of preliminary testing [65, 66]. Simulation tools offer a versatile technique to assess data center energy efficiency. It only takes a quick assessment of energy efficiency on a simulated cloud computing system. It can assess not only existing systems but also those that have yet to be developed. CloudSim [41] and GreenCloud [42] are two of the most used simulation tools. CloudSim was developed by the Grid Lab and the Gridbus project of the University of Melbourne, Australia. In order to make up for the shortcomings of CloudSim, most of the newly developed simulation tools have been extended on the basis of CloudSim to meet the special needs of data centers [67, 44, 48, 43]. Table 3 shows the existing simulation tools. Simulation tools have obvious flaws. The use of simulation tools to evaluate energy efficiency, according to Kafhali et al. [33], necessitates independent numerous runs of simulation models to preserve the effects of varied input settings, which is time-consuming and can lead to incorrect results. Furthermore, there are some flaws in the simulation platform's energy consumption model. As a result, using simulation methodologies to assess the energy efficiency of cloud data centers is not recommended. However, in certain instances, it can be used as a preliminary test.

2.3. Analytical modeling-based evaluation

Analytical modeling-based evaluation employs mathematical techniques to create appropriate models that abstract the system (whether it exists or not) and define the link between performance, energy consumption, and load. It significantly decreases the burden associated with evaluating energy efficiency. The determination of model parameters is based on the system's measurement findings or a parameter guess that differs from the real metrics. The accuracy of performance and energy consumption metrics depends on the accuracy of the model. Simplifications and assumptions are common in analytical modeling-based evaluation methodologies. Faced with various behaviors of complex systems, it lacks the ability to describe the details of the system. One strategy to increase the model's performance is to employ more characteristic variables to represent the system's specifics. However, simply adding feature variables to a model does not guarantee that it will improve. Because some factors will have a detrimental impact on the model's performance. More researchers are turning to highly reliable

[1] https://www:cee1:org/LearningAboutEvaluation

Table 3
Simulation analysis of performance and energy consumption

Simulation tools	Study focus	Ref
CloudSim	Performance of cloud resource allocation strategies, application workload models, and resource performance models	[41]
GreenCloud	Work load distribution, component energy consumption in the data center, and packet-level communication mode	[42]
ThermoSim	Thermal perception of cloud data centers nodes based on deep learning	[43]
AutoScaleSim	Supports automatic extension of web applications in a customizable, extensible and scalable manner in a cloud environment	[44]
SinergyCloud	Evaluate hybrid cloud scenarios with fine abstract granularity, including energy consumption, workflow completion time, task completion time, and virtual machine migration	[45]
IoTSim-Osmosis	In a heterogeneous edge cloud environment, support penetration computing for complex IoT applications	[46]
MT-EA4Cloud	Check the correctness of the cloud system from the perspective of energy-aware and optimize its energy consumption	[47]
MultiRECloudSim	Extend CloudSim to implement multi-resource scheduling and power consumption modeling	[48]

Table 4
Modeling high availability to analyze performance and energy

Modeling method	Study focus	Ref
Stochastic Reward Net(SRNs)	Investigate data center performance and QoS in IaaS Clouds	[49]
Queue theory Markov chain	Analyze performance and energy consumption in cloud data centers	[33]
Stochastic model based on Queueing theory	Stochastic modeling of dynamic right-sizing for data center efficiency	[50]
Bayesian networks	Allocation of cloud resources	[51]
Probability distribution	Model the accumulated downtime	[52]
Statistical distribution	Model a service-based market	[53]
K-means and TOPSIS	Building energy performance evaluation and ranking	[54]
Emergy analysis	Energy consumption of data center cooling system	[55]
Machine learning	Energy efficiency based on changes in behavior	[56]
Machine learning	Assess the load and energy consumption of the data center	[57]
K-type clustering algorithm	Develop a dynamic room-level energy benchmark test method	[58]
Grey model and risk evaluation model	Energy security in China	[59]
Mixed multi-criteria decision	The economic-environment-energy (3E) performance of the CCHP-MG system	[60]
Data analysis	Data center dedicated cooling system	[61]
Neural network and fuzzy comprehensive evaluation method	Carbon efficiency performance evaluation	[62]
Data mining	Anomaly detection and dynamic energy performance evaluation of HVAC systems	[63]
Energy decomposition	Energy performance of district heating substations	[64]

approaches to develop cloud models and examine the trade-offs between performance and energy efficiency [2, 55, 57, 61]. Table 4 shows some representative analytical modeling-based evaluation methodologies. Machine learning, particularly deep learning, can abstract complex systems better than typical methods. As a result, academics are attempting to simulate using machine learning [56, 57, 62].

3. Energy efficiency evaluation metrics

Energy efficiency metrics are the measurement standard of energy efficiency evaluation, which are beneficial for operators to better understand potential inefficiencies and improve their performance by analyzing core parameters [68]. It's useful to promote industry innovation and environmental sustainability goals for researchers and practitioners in data centers. Therefore, research on energy efficiency metrics is the focus of energy efficiency evaluation. In 2017, Reddy et al.[11] analyzed 132 sustainability-related metrics of data centers. From the perspective of data center operations, energy efficiency metrics mainly included cooling, performance, sustainability, air management, security, financial impact (data center energy changes, carbon, oil price changes), etc. At the same time, they analyzed the relationship between metrics. The summary contained the

Table 5
Coarse-granularity metrics

Metric	Name	Description	Ref
PUE	Power Usage Efficiency	Power Usage Efficiency is the current main energy efficiency metric of data centers	[35]
DCiE	Data Center Infrastructure Efficiency	A performance improvement metric used to calculate the energy efficiency of a data center	[72]
DCeP	Data Center Energy Productivity	It incorporates both the infrastructure and the IT equipment when evaluating data center energy efficiency	[73]
CADE	Corporate Average Data Center Efficiency	Performance metric that evaluate the energy efficiency of a data center can be used to measure the performance of IT equipment and facilities, and can be compared with the performance of other data centers	[74]
TUE	Total-Power Usage Effectiveness	TUE is defined as the ratio of total energy consumption to the specific energy used by the computing components, which makes up for the shortcomings of PUE	[75]
DCPE	Data Center Performance Efficiency	DCPE is defined as the ratio of useful work to the total facility power	[76]

most common energy efficiency metrics except IPA(the Infrastructure Power Adaptability), PVar(the Power Variability) [69], and OEF(On-site Energy Function), OEM(On-site Energy Matching) [70]. The work in [15] and [11] has comprehensively collected and analyzed many data center energy efficiency metrics, which can be used as a data center metric manual.

3.1. Classification of metrics

The structure of a modern cloud data center is quite complex and involves many IT equipments and infrastructures. With such a complicated structure, defining energy efficiency evaluation metrics that are adaptable is quite difficult. Besides, the measurability of metrics in practice must be considered. The existing energy efficiency evaluation metrics of data centers can be divided into the following three categories from granularity: coarse-granularity metrics, medium-granularity metrics, and fine-granularity metrics [71].

3.1.1. Coarse-granularity metrics

Many metrics have been proposed at the level of the entire data center by researchers. These metrics are a little rought, but they're easy to come by. PUE [89] is a typical metric that assesses data center energy efficiency as a ratio of total data center energy consumption to energy consumption of IT equipment, which is relatively concise compared to other metrics. The representative coarse-granularity energy efficiency evaluation metrics are summarized in Table 5. These metrics are popular because they employ only one metric to evaluate the data center's total energy efficiency, which eliminates the need for several details in the data center. However, because energy efficiency details of data center sub-components are lacking, the evaluation results cannot be used to advise data center energy savings.

3.1.2. Medium-granularity metrics

Researchers have proposed a significant variety of medium-granularity metrics for data center components. The energy consumption behavior of data center subcomponents is ignored by coarse-granularity metrics. To compensate for the lack of coarse-granularity metrics, medium-granularity metrics give energy efficiency information for specific equipment, infrastructure, and green energy in the data center. Table 6 summarizes the representative medium-granularity energy efficiency metrics by IT equipment, cooling equipment, and green energy. Medium-granularity metrics can evaluate the energy efficiency of data centers more accurately and extensively than coarse-granularity metrics due to their diversity and pertinence.

3.1.3. Fine-granularity metrics

The fine-granularity metrics[2] provide detailed performance information for specific components in data centers. These components are IT equipment responsible for the normal operation of data centers, such as CPU, disk, memory, network, and storage. These performance metrics cannot directly represent data center energy efficiency, but they may be evaluated by looking at changes in performance and energy consumption, which can be seen through the performance/watt rate. The fine-granularity metric of energy efficiency evaluation is the most significant thing for cloud operators. Users are mainly interested with performance metrics, and operators seek to deliver improved services while decreasing energy use to the greatest extent possible. Coarse-grained and medium-grained energy efficiency evaluation methods often ignore the needs of customers. The representative data center fine-granularity metrics is summarized in Table 7.

[2] https://docs.vmware.com/

Table 6
Medium-granularity metrics

Type	Metric	Full Name	Description	Ref
IT Equipment	ITEE	IT Equipment Energy	Measurement of IT Equipment Energy.	[77]
	SCE	Server Compute Efficiency	Determining whether the server is performing tasks and measuring the proportion of useful work.	[78]
	DWPE	Data center Workload Power Efficiency	Energy efficiency ratio of a specific workload and the overhead for operating a given system in a certain data center.	[79]
	EPI	Energy Proportionality Index	It depicts the proportional relationship between energy consumption and load.	[80]
	ITEU	IT Equipment Utilization	Characterizing the operating efficiency of IT equipment in data centers.	[77]
	TGI	The Green Index	Evaluation of the energy efficiency of severs based on various existing benchmark tests, Weights, such as time, energy and consumed power.	[81]
	CNEE	Communication Network Energy Efficiency	Ratio of power consumed by network equipment and effective network throughput capacity, which is used to evaluate the energy of delivering a single message.	[82]
	NPUE	Network Power Usage Effectiveness	Ratio of total power consumed by IT equipment and power consumed by network equipment.	[82]
Cooling Equipment	COP	Coefficient of Performance Ensemble	Ratio of total power consumption of HVAC equipment to power consumption of IT equipment.	[83]
	RER	Renewable Energy Ratio	Measurement of the utilization of renewable energy in data centers.	[84]
	DCCSE	Data Center Cooling System Efficiency	Evaluation of the efficiency of the HVAC system in terms of power used per unit of cooling output.	[85]
	MLC	Mechanical Load Components	Ratio of total power consumption of HVAC equipment to power consumption of IT equipment per year.	[86]
	CLF	Cooling Load Factor	Ratio of cooling equipment power to IT equipment power.	[83]
Green Energy	WUE	Water Usage Effectiveness	Evaluation of water usage efficiency in data centers.	[87]
	CUE	Carbon Usage Effectiveness	Evaluation of carbon usage efficiency in data centers.	[88]
	ERE	Energy Reuse Effectiveness	Measurement of the reused energy. Ratio of energy other than reused energy to IT equipment energy.	[84]
	GEC	Green Energy Coefficient	Ratio of renewable energy used to total power consumption.	[77]

Table 7
Fine-granularity metric

Type	Name	Description
CPU	CPU Utilization	Proportion of CPU working time in total time
	CPU Workload Balance Factor	Measuring the ability to allocate tasks across multiple operating units
	Waiting Time	Waiting time of each process in the ready queue
Disk	Usage Rate	Sum of the average read data and written data of all disk instances of hosts or virtual machines
	Commands Per Second	Average number of commands issued within a time interval per second
Memory	Memory Usage	Memory usage of hosts
Network	Throughput	Maximum data rate that devices can accept and forward
	Data Transmission Speed	Average amount of data transferred per second
Storage	Storage Usage Average	Total throughput rate

3.2. Advantages and disadvantages of metrics

Coarse-granularity metrics focus on the overall energy consumption behavior of the data center while overlooking specific nuances. Medium-granularity metrics are used to supplement coarse-granularity metrics and focus on data center sub-component energy consumption behavior. The majority of fine-granularity metrics are tied to IT equipment and cannot be used to determine energy efficiency directly. For data center researchers and practitioners, there are currently hundreds of data center energy efficiency metrics. In order to select appropriate metrics for energy consumption evaluation, we also need to understand the advantages and disadvantages of different metrics.

Table 8
Advantages and disadvantages of data center metrics

Metric	Advantages	Disadvantages
PUE	Evaluation metrics recognized by the industry, easy to measure	Too simple, without considering the details
DCiE	The inverse value of PUE , easy to measure	Unable to capture small changes
DCeP	Closest to the definition of energy efficiency	Difficult to measure
CADE	Can be used for data center performance comparison	Difficult to measure and complicated to calculate
TUE	Solving the problem that PUE increases when hardware energy consumption is reduced due to the development of technology	Hardware energy consumption is difficult to measure and can only be predicted
DCPE	Can measure data center performance efficiency	Difficult to define useful work and measure
WUE	Increase the evaluation of water use to make up for the lack of PUE	The calculation process is cumbersome
CUE	Pay attention to the sustainability of the data center's carbon footprint	Carbon dioxide emissions are difficult to accurately estimate
EPI	Pay attention to the proportion of energy in the data center	Difficult to use load to represent hardware utilization

3.2.1. Advantages and disadvantages of important metrics

Fine-granularity metrics cannot directly evaluate the energy efficiency of data centers. They are not commonly used. Currently, the industry mostly uses coarse-granularity metrics or medium-granularity metrics to evaluate data centers energy efficiency. Table 8 summarizes the advantages and disadvantages of some important metrics. PUE is one of the most extensively utilized metrics in the industry. This metric will be discussed further below.

3.2.2. Advantages and disadvantages of PUE

At present, data centers still use PUE as the main measurement standard for energy efficiency evaluation. It offers a number of advantages, including ease of measurement and promotion, and its calculation method is not limited by servers, storage capacity, or data center construction. However, as the data center industry has grown, so have the demands for great energy efficiency and long-term sustainability. PUE has gradually revealed some flaws. There are many specific studies aimed at improving PUE [90, 91, 92]. We summarize the disadvantages of PUE to help related researchers improve it.

The disadvantages of PUE can be summarized as follows:

(1) PUE merely summarizes the overall energy efficiency of data centers. It lacks practical guidance due to a lack of detail. Based on the evaluation results of PUE alone, we have no way to know how to improve the energy efficiency of data centers.

(2) According to the definition of PUE, we fail to know the energy efficiency of IT equipment from the metric [12]. While IT equipment is exactly the backbone of data centers. When we try to improve IT equipment for efficiency, we don't know where to start. It's unknown whether all the electricity used by IT devices yields beneficial output. In terms of the value of PUE, the productivity of the data center is a mystery.

(3) In order to meet the requirements of sustainable energy development. The energy efficiency evaluation of the modern data center industry not only evaluates the energy efficiency utilization of data center IT equipment, but also reflects multiple aspects such as water utilization, carbon utilization, and renewable energy utilization. It is impractical to try to use one indicator to cover all aspects of data center energy efficiency. What is important is that researchers need to pay attention to the impact of energy efficiency on green resources. Therefore, we need to find better energy efficiency evaluation methods.

(4) With the advent of virtualization technology, the energy efficiency of data centers has improved. However, if the scale of infrastructure is not compatible with the reduction of the overall load, the efficiency of infrastructure will be reduced. In this case, the result of PUE will be worse, which shows that PUE has great limitations as a measurement standard [93]. Van et al. [70] summarized the impact of IT load on PUE. First, the value of PUE was better when the IT load was relatively high [94]. Second, when more efficient IT devices were installed, the drop in average IT load will cause a drop in PUE [95]. While PUE is only used to measure the efficiency of the physical infrastructure architecture in data centers, rather than IT computing power efficiency. It's a failure to reflect obvious environmental benefits after reducing energy consumption, which is a serious defect as a widely used metric of energy efficiency.

(5) PUE considers the energy used for cooling regardless of temperature. As a result, it is theoretically impossible to compare different data centers [90]. To reduce the cost of thermal energy, Microsoft in the United States chose to sink the data center to the ocean floor. And China's Tencent reduced cooling costs by digging holes. It can be seen that the effect of temperature on the energy efficiency of data centers cannot be ignored because of the climate difference in different regions. And PUE's

original purpose was never used for comparison, but it is currently used for this purpose [11]. Because much more energy burden is invested to cool the data center in tropical regions than that in freezing regions, it is unreasonable to use PUE to perform a unified energy efficiency evaluation comparison under huge temperature differences.

4. Status and challenges of energy efficiency evaluation

4.1. Status of energy efficiency evaluation

In order to improve the energy efficiency of data centers, the data center industry and researchers have developed a large number of energy efficiency evaluation techniques. The efforts of industry and researchers have had a positive impact on data center energy efficiency. To help the industry and researchers further improve the energy efficiency of data centers, we analyzed the current status of energy efficiency evaluation in industry and academia.

4.1.1. Data center industry

The industry has been working on energy efficiency evaluation metrics for many years. The Green Grid Organization proposed the principles of measuring DCeP, PUE, GEC, ERF, and CUE [96]. ISO and IEC have established a number of standards for energy efficiency evaluation criteria in recent years. In 2016, they formulated standards for key performance metrics for data centers, and proposed that key performance metrics must cover the effective use of resources and reduce carbon dioxide emissions [97, 98]. In the latest research, they have developed data center server energy efficiency metrics (SEEM) [99] and application platform energy effectiveness (APEE) [100] standards to improve key performance metrics. The CEN/CENELEC/ETSI Green Data Center Coordination Group defined data center design standards in their most recent report, stating that the industry must set greater targets for energy management and environmental feasibility in the future [101]. For example, the influence of air pollution, condensation, and toxic negative products on data centers. Standards for evaluating data center energy efficiency have always been developed by the industry, not by academics.

With the joint efforts of many stakeholders, relevant data shows that the PUE value has been declining year by year [102]. With the development of science and technology, it is a question of whether the past energy efficiency evaluation technology is suitable for new data centers. Moreover, some facts indicate that the energy consumption of data centers will still increase substantially [103]. With the increase in the number of computing instances, the proportion of servers in ultra-large-scale data centers continues to increase [9, 104, 105]. The energy efficiency benefits of servers are not enough. As a result, the industry has a long way to go in terms of improving data center energy efficiency.

4.1.2. Energy efficiency research

Hundreds of metrics have been devised by researchers to evaluate data centers, however they are rarely used. In the early period, an unprecedented survey on the application of data center efficiency metrics was described by Procaccianti G et al. [106]. The results showed that less than a third of the respondents (461 out of 1523 respondents) knew about data center efficiency metrics. Most employees in the data center industry lacked awareness of evaluation metrics. Researchers did another similar poll four years later [15], and many data center personnel still knew very little about energy efficiency evaluation metrics.

As mentioned above, the research results are out of touch with industrial production. The lack of understanding of energy efficiency metrics makes it difficult to keep up with the pace of technological change. Only when energy efficiency metrics are properly pushed is an academic study on energy efficiency worthwhile.

Furthermore, rather than the thorny challenges encountered in the data center industry, the research of energy efficiency evaluation should be based on actual requirements. The most effective technique to determine the most appropriate assessment method is to do a specific study for each problem. However, it is regretful that much energy efficiency evaluation work is restricted to academia, leaving it utterly disconnected from decision-makers and businesses.

4.1.3. Misuse of metrics

One of the great problems on data center energy efficiency evaluation in the twenty-first century is the misuse of energy efficiency metrics [107]. For example, PUE plays a significant role in the energy efficiency evaluation by environmental protection personnel. When taking climatic factors into account, if the local perennial temperature is high, this means that more energy needs to be consumed for cooling. In this case, the PUE evaluated will conclude that the data center should not be established. However, because the PUE was designed to quantify the energy efficiency of data center infrastructure, the results of measuring data center energy efficiency using the PUE after server integration are unreliable. It can be seen that different application scenarios require different energy efficiency metrics in data centers to evaluate energy efficiency. Misuse of metrics may adversely affect the operation management of data centers and the research of scholars.

Green Grid clearly stated in the PUE white paper that it is not recommended to use PUE to compare different data centers [35]. However, the PUE has become a unified standard in the industry, and people have forgotten whether it can be used to compare different data centers. The internal structure of different data centers is different, and the corresponding measurement methods are also different. The abuse of metrics has brought disasters to the data center energy efficiency evaluation.

4.2. Challenges of energy efficiency evaluation

At present, the energy efficiency evaluation of data centers has not yet formed a systematic theory, and there is no set of universal standards. Most of the metrics in Section 3 need to be measured from the actual data center, but due to the difference in the structure of the data center, there are many limitations in energy efficiency evaluation.

Most of the data center energy efficiency metrics are aimed at a local system or a specific target, which lacks practicality. The shortcomings of this data center energy efficiency rating approach can be attributed to a variety of factors. For starters, establishing universal energy efficiency evaluation standards is difficult due to the diversity and complexity of data center structures. In data center construction, many elements must be addressed, including geographic location, floor area, local climate, construction scale, and interior design. Second, the technology for measuring data center energy efficiency has yet to be broken. Third, there is no worldwide body that plans data centers and establishes common standards for data centers in different nations.

Most of the current energy efficiency evaluation standards are mainly developed for existing physical data centers. A large number of researchers expect to have an omnipotent data center energy efficiency evaluation metric or method, which can reflect both the energy efficiency of infrastructure and IT equipment. However, It is really difficult to have both. These two parts are important components of data centers. They are not mutually restricting nor antagonistic, despite the fact that they are not fully separated. The energy efficiency of IT equipment will not be sacrificed for cooling, and vice versa. The relationship between the two is that cooling equipment is the same as the various facilities performing duties in the data center, as auxiliary equipment for IT equipment. So, the energy evaluation metric is specifically aimed at IT equipment shall be designated for the desire to reflect the energy efficiency of IT equipment.

All in all, it's impossible to expect that an energy efficiency metric of data centers can reflect the energy efficiency of IT equipment and carbon utilization rate, water utilization rate, heat recovery, renewable energy utilization rate, cooling efficiency, safety, etc. A metric can be regarded as a specific metric for a specific problem. For example, a major issue requires large and general metrics, while a subtle issue requires refined metrics. Regarding the energy efficiency evaluation of a modern data center, many energy efficiency issues need to be considered, such as improving the utilization rate of renewable energy, improving cooling efficiency, etc. We can specify a metric system to evaluate the energy efficiency of data centers, instead of trying to use an evaluation metric replacing PUE to apply contents in many aspects like IT equipment utilization rate, carbon utilization rate, water utilization rate, renewable energy utilization rate. Fernando et. al [21] made a good demonstration, who developed a set of metrics to evaluate the overall energy efficiency of data centers, calculated metrics by using accumulated energy requirement as a resource metric and then analyzed metrics through the life cycle of products.

5. Proposals for energy efficiency evaluation

Energy efficiency metrics are the flesh and blood of energy efficiency evaluation. In response to the challenge of energy efficiency evaluation, we propose several methods to improve the existing evaluation methods of data centers. We advocate initially enhancing the PUE performance because it is now the most essential energy efficiency evaluation method and the ancestor of energy efficiency evaluation. At the same time, we pointed out that new metrics should be devised to address the industry's shifting issues. Finally, to completely capture the specifics of data center energy efficiency, we offer a multi-metric fusion method.

5.1. Improvements of the PUE

Although the PUE has many defects (Section 3.2.2), it has been greatly promoted due to the simplicity of the model. The PUE is still a retrospective metric, in essence, based on the values measured by data center operators, and it cannot explain the potential factors that determine the PUE value (such as installed equipment and operator decisions, etc) [108]. Some researchers tried to improve PUE to promote cloud operators and decision-makers to better make data center strategies. Voort [109] used supplementary metrics to find the potential of energy efficiency metrics outside the scope of PUE. In order to better evaluate energy efficiency, the GUE (grid utilization efficiency) was introduced. But instead of verifying the general model against actual PUE data, it is a simplified calculation to compare the theoretical PUE reduction under different natural cooling assumptions. Google [110] has tried to apply machine learning to data center optimization. This model can predict PUE through learning from actual operational data and achieve a 0.4% error. This method needs a huge number of non-public data sets, making replication and promotion challenging.

Nuoa Lei et al. [108] conducted the most comprehensive study, developing a statistical framework for predicting and analyzing data center power usage efficiency (PUE) based on the thermodynamic PUE model. Climate variables and energy system parameters are input into the PUE prediction model. The PUE value is predicted under uncertainty and verified using the reported values of real data centers. These studies all have considered the temperature factors which have a significant impact on data centers and minimized the impact of climate differences and seasonal changes on the accuracy of the energy efficiency evaluation results. In fact, the PUE energy efficiency model based on simple measurements is outdated. It is necessary to consider the factors of differences in temperature and system parameters in data centers to improve the PUE to meet the rapid development of data centers. Additionally, it is recommended that different data centers should be graded, and PUE can be compared among different data centers after being rated as different levels of size.

5.2. Development of new energy efficiency metrics

Organization that develops data center evaluation metrics: standardization bodies, industry groups, professional bodies, and local, regional, and international government agencies. It is strongly believed that all the proposed metrics are usually not applied consistently across the globe, so appropriate general methods and calculation standards are required. In order to meet the needs of different stakeholders, researchers have tried to improve the existing energy efficiency metrics, but these are not enough to meet the new changes and challenges. In [111], several metrics were used to analyze the energy and cooling efficiency of small data centers in real-time. The authors came to the conclusion that new energy efficiency metrics need to be developed to evaluate the energy efficiency of data centers. For example, a new metric may be considered to be an extension of the work done by Cao et.al [112], which is on the basis of the two metrics of OEM(On-site Energy Matching) and OEF(On-site Energy Fraction) [113]. They are shown as Equation (1) and Equation (2), respectively.

$$OEF = \frac{\int_{t1}^{t2} Min\,[G(t); L(t))]\,dt}{\int_{t1}^{t2} (L(t))dt}; \quad 0 \leq OEF \leq 1. \quad (1)$$

$$OEM = \frac{\int_{t1}^{t2} Min\,[G(t)); L(t)]\,dt}{\int_{t1}^{t2} G(t)dt}; \quad 0 \leq OEM \leq 1. \quad (2)$$

Where $G(t)$ represents on-site generated power (kW) at time t and $L(t)$ represents load power (kW) at time t, and $t1$ and $t2$ represent the start and end of an energy efficiency evaluation in a given time period, respectively. These two metrics are used to evaluate mismatch problems between on-site renewable energy production(such as heat recovery in a data center, solar, and wind) and original configuration load. Yuventi et al. [114] proposed that PUE could only roughly convey the lowest possible energy consumption, but could not accurately convey the information over a period of time. Most of the new energy efficiency evaluation metrics proposed by researchers may appear in an integrated form in the future.

It is worth mentioning that, according to [89], PUE has been used as a mainstream approach for determining the energy efficiency of data centers in the global technology industry. Despite the PUE having some shortcomings, it is still an optimal energy efficiency evaluation method until a better alternative evaluation metric appears.

5.3. Multi-metric evaluation

Obviously, it is not objective enough that use a single metric to comprehensively evaluate the energy efficiency of a data center. The difference is that multi-metric evaluation can more accurately and comprehensively reflect the energy efficiency of the data center in some details because it comprehensively considers various dimensions and weighs different metrics. We assume that DCEE represents data center energy efficiency, which can be represented as Equation (3).

$$\begin{aligned} DCEE = \beta_1 * ITEU + \beta_2 * CUE + \beta_3 * WUE \\ + \beta_4 * DCCSE + \beta_5 * ERE + \beta_6 * PUE. \end{aligned} \quad (3)$$

Where ITEU denotes the IT equipment utilization, CUE is the carbon usage effectiveness, WUE is the water usage effectiveness, DCCSE is the data center cooling system efficiency, ERE is the energy reuse effectiveness, PUE is the power usage effectiveness, and $\beta_k (k = 1, \ldots, 6)$ represents the weight of the corresponding metric.

The selected metrics in Equation (1) are mainly from the perspective of green energy, as possible to achieve green data centers. Environmental protection plays an important role in global sustainable development, especially in the case of larger data centers. So establishing a new energy efficiency evaluation system is a common expectation of people.

The multi-metric energy efficiency evaluation process for data centers can be shown in Figure 3, which is designed by referring to the multi-objective decision-making methods in the sustainable energy decision [115]. The multi-metric energy efficiency evaluation process mainly includes four steps: determination of evaluation metrics, data processing, determination of metric weights, and combination of metrics and weights.

5.3.1. *Determination of evaluation metrics*

In multi-metric evaluation, we can't mix metrics at will because they usually have a limited scope of application. Not all metrics are suitable for multi-metric fusion. The selection of metrics follows several important rules:

- Metrics are numerical values that can be measured. Metrics measurement should not take up too much time or resources, and it should not disrupt normal operations.
- Metrics are oriented. The metrics aim to optimize the performance of the data center and have a traceable improvement direction.
- Metrics are independent. In the metric system, there is no overlap between metrics and no inclusion relationship.
- Metrics are practical and generalized. The measurement scale and granularity of metrics should meet the actual evaluation needs and can effectively measure multiple data centers, extensively.
- Metrics should be reliable and adaptable to changes in the data center's state.

5.3.2. *Normalization of metrics*

Different energy efficiency metrics have different dimensions and orders of magnitude. Therefore, when the level difference between metrics is large, if the original metric value is used for comprehensive evaluation, the role of higher value metrics in the a comprehensive evaluation will be highlighted, and the role of lower value metrics will be relatively weakened. To ensure the reliability of the evaluation results, it is necessary to normalize the original energy efficiency metric data. There are many methods for data normalization, the most popular are the min-max

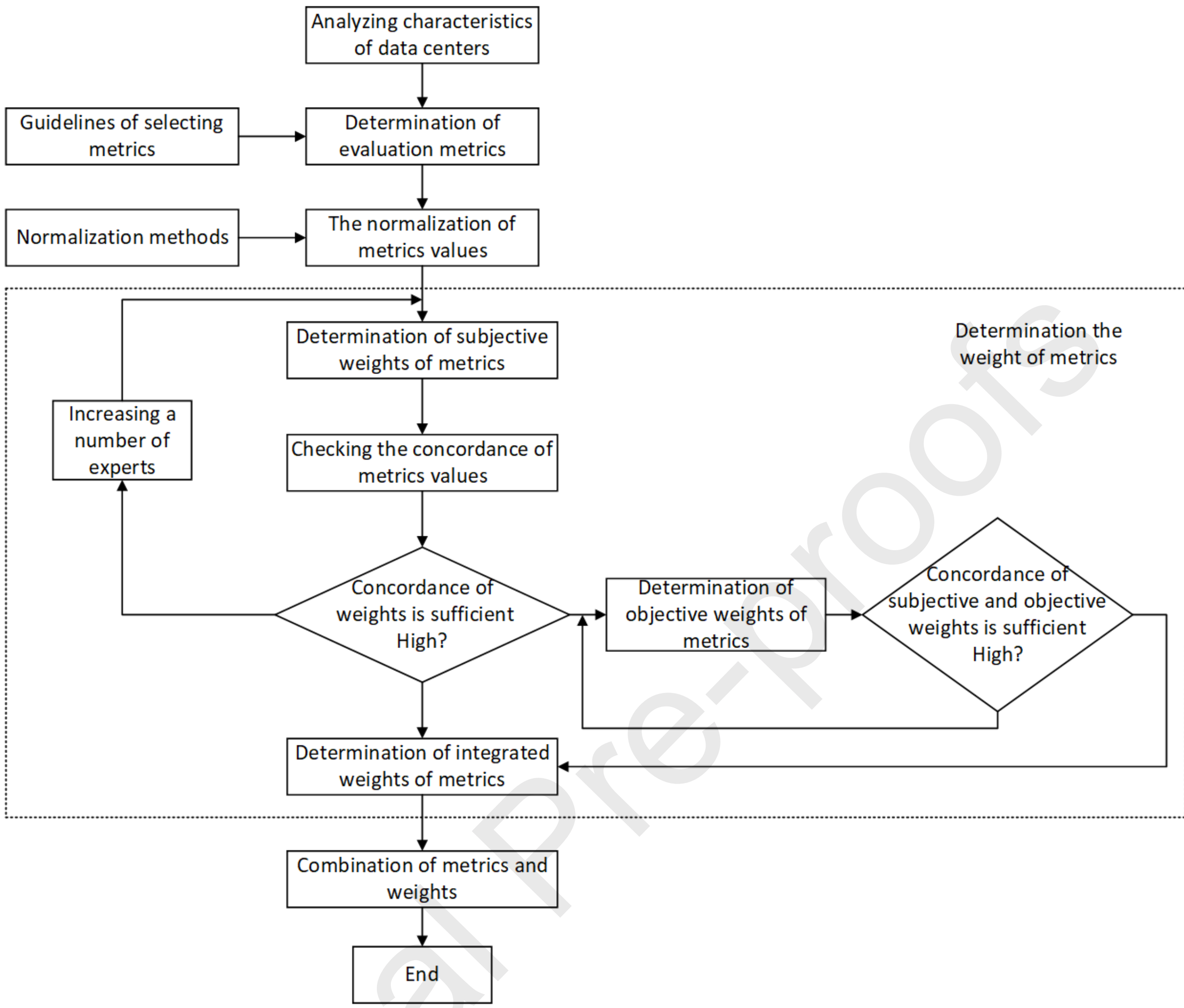

Figure 3: Multi-metric energy efficiency evaluation process for data centers.

normalization and Z-score normalization. We assume that the original data set is defined as $X = \{x_1, x_2, \dots, x_n\}$ and the processed result is $Y = \{y_1, y_2, \dots, y_n\}$.

Min-max normalization: Min-max normalization is also called dispersion normalization in data processing. The transforming relationship is shown as Equation (4).

$$y_i = \frac{x_i - \min\limits_{1\le j\le n}\{x_j\}}{\max\limits_{1\le j\le n}\{x_j\} - \min\limits_{1\le j\le n}\{x_j\}}. \tag{4}$$

Where $\max\limits_{1\le j\le n}\{x_j\}$ is the maximum value in X, $\min\limits_{1\le j\le n}\{x_j\}$ is the minimum value in X and each y_i falls into the interval $[0, 1]$. This method retains the existing relationships in the original data and is the easiest way to eliminate the influence of dimensions and data range. When new data is added, the maximum and minimum values may change and need to be redefined. If a certain number in the value set is too large, the normalized values are close to 0, and the difference between these values is small.

Z-score normalization: Z-score normalization is one of the most popular normalization methods, also known as standard deviation normalization. The results of data normalization are not all mapped into the interval $[0, 1]$, which is different from the min-max normalization method. The normalization formula is shown as Equation (5).

$$y_i = \frac{x_i - \overline{x}}{s}. \tag{5}$$

Where $\overline{x}$ is the mean of the sample and $\overline{x} = \frac{1}{n} * \sum_{i=1}^{n} x_i$, s is the standard deviation of the sample and $s = \sqrt{\frac{1}{n-1} * \sum_{i=1}^{n}(x_i - \overline{x})^2}$.

This method normalizes the data based on the mean and standard deviation of the original data. It is extremely applicable when the maximum and minimum values in the original data set are unknown, or there is a value that exceeds the value range. After normalization, values of the variable fluctuate up and down around 0. Values larger than 0 indicate a higher value than the average, while values less than 0 indicate a lower value than the average.

5.3.3. Determination of metric weights

Weighting is a very important step in multi-index energy efficiency evaluation. The size of the weight indicates the importance of the corresponding metric, so different weight distributions will produce different values of energy efficiency evaluation, and reasonable weight can truly reflect the true situation of data center energy efficiency. There are three commonly used weighting methods, subjective weighting, objective weighting, and combining subjective and objective weighting.

Subjective weighting: Representative methods for setting subjective weights are analytic hierarchy process(AHP) [116] and Delphi [117]. In [118], authors studied the cloud computing data center adopting factors validity by fuzzy AHP successfully. Subjective empowerment may be self-contradictory, and a consistency test needs to be added [119]. The Delphi method is an anonymous feedback inquiry method. Both methods are time-tested and are very mature and reliable weighting methods. They require experts in the industry to judge or score various metrics. Although they are subjective methods, multiple experts repeatedly perform this work to ensure the credibility of the weight setting. Moreover, experts can comprehensively consider the actual factors, so the weights will be more in line with actual situations. In the later stage, In order to form a unified standard, there is still needing an organization to call on data centers industry experts all over the world to communicate.

Objective weighting: Commonly used objective weighting methods usually include principal component analysis, entropy weight method, and mean square deviation method, multi-objective planning method. The objective weight is mainly coming from sample data, which eliminates the interference of subjective factors. However, objective weighting methods are also limited by sample data. When the sample data changes, the weight will also change, and the influence of outliers on the weight cannot be eliminated. In order to make the objective weighting effect more excellent and stable, the sample data must be large enough. At this stage, using data science methods, such as neural networks, linear regression, etc., to perform deep learning on samples to obtain objective weights is a relatively leading method. However, it takes huge manpower, material resources, and financial resources to obtain enough measurement data of energy efficiency metrics in cloud data centers. And the measurement methods of energy efficiency metrics are also controversial and have not yet reached an agreement in the industry. The premise of the intelligent weighting methods is difficult to achieve. So it is extremely difficult to use these methods to weigh multiple metrics, and it is still a vacancy at present. This shows that it is very important to define a unified data centers construction standard. Which is not only conducive to industry specifications but also the establishment of a unified energy efficiency evaluation standard.

Combined weighting: Subjective weighting methods are closer to reality but are affected by the subjective preference of the decision-makers. Because the judgment of decision-makers mainly depends on their knowledge or information, but subjectivity will affect the accuracy of the results. On the contrary, objective weighting methods obtain more scientific results by analyzing the original measurement data. But the weighting methods are too dependent on the sample. Although these two methods have a certain degree of information loss, the combination of subjective weight and objective weight can minimize information loss and make the weighted result as close to the actual result as possible. Subjective and objective weights are usually combined with multi-metric evaluation methods, such as the cloud model method, fuzzy comprehensive evaluation method, gray correlation evaluation method. The above objective weight methods can be found in [115]. Among them, the grey correlation method is more commonly used in energy systems [120, 121].

Data centers have complex structures and different scales, making it difficult to establish a unified universal energy efficiency evaluation metric system. The current multi-index evaluation of data centers energy efficiency still uses multiple metrics to classify the data center. The data center energy efficiency evaluation based on the integration of multiple metrics has not been adopted in reality. Moreover, the diversity of data center structures makes the multi-metric evaluation not suitable for the evaluation of data centers with a global concept. Multi-metric evaluation is suitable for evaluating the energy efficiency of a single data center or comparing the energy efficiency of similar data centers.

6. Summary

The commercial use of 5G and the rise of artificial intelligence had promoted the development of the digital economy. As one of the pillars of the digital economy, data centers have brought amazingly high energy consumption while growing rapidly. In order to promote sustainable development and improve the energy efficiency of data centers, researchers have developed a large number of energy efficiency evaluation metrics and some energy efficiency evaluation methods.

By evaluating the majority of the data center energy efficiency evaluation research experience, this paper described the energy efficiency evaluation techniques and three granular metrics. At the same time, we looked at the benefits and drawbacks of various evaluation methodologies and metrics, particularly the power usage efficiency (PUE). Then we addressed the current state of energy efficiency evaluation and the challenges it faces, as well as some potential improvements. PUE is the most often used evaluation metric today. To adapt to the fast-changing data center, we recommend boosting PUE performance. At the same time, we advocate for the creation of new metrics. The result of the multi-metric evaluation is more objective than the result of evaluating the data center by a single metric. We urge that data centers be evaluated using a multi-metric approach more often.

The data center industry, decision-makers, and academia have all made significant contributions to the evaluation of energy efficiency. Energy efficiency evaluation still has a long way to go, as evidenced by data centers' ever-increasing energy use. Academia should pay close attention to industry and integrate study findings from energy efficiency assessments into practice. Simultaneously, academics and industry should promote new technology aggressively in order to prevent its misuse. Renewable and alternative energy should be taken into consideration by data center operators. While boosting energy efficiency, the data center's carbon emissions are reduced. Studies have pointed out that, compared with large data centers, most of the energy consumption of data centers is consumed by small and medium data centers [23]. The majority of small and medium-sized data centers use outdated energy-saving technologies. Decision-makers should keep the number of small and medium data centers under control so that they are forced to use more energy efficient technologies.

The data center industry is responsible for developing energy efficiency evaluation standards. Energy efficiency has been enhanced to some extent thanks to the combined efforts of numerous stakeholders. However, data center operators, decision-makers, and academics must maintain their efforts in the face of rising energy usage. As the two largest power consumers in data centers, infrastructure (non-IT equipment) and IT facilities, both need to considerably increase energy efficiency. In the future, we may put more effort into energy efficiency modeling, energy-saving technologies, promotion of energy efficiency evaluation criteria, and the utilization of renewable resources to create more sustainable green data centers.

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